

Text Recognition in the Wild: A Survey

XIAOXUE CHEN*, LIANWEN JIN*, YUANZHI ZHU, CANJIE LUO, and TIANWEI WANG, the College of Electronic and Information Engineering, South China University of Technology, China

The history of text can be traced back over thousands of years. Rich and precise semantic information carried by text is important in a wide range of vision-based application scenarios. Therefore, text recognition in natural scenes has been an active research field in computer vision and pattern recognition. In recent years, with the rise and development of deep learning, numerous methods have shown promising in terms of innovation, practicality, and efficiency. This paper aims to (1) summarize the fundamental problems and the state-of-the-art associated with scene text recognition; (2) introduce new insights and ideas; (3) provide a comprehensive review of publicly available resources; (4) point out directions for future work. In summary, this literature review attempts to present the entire picture of the field of scene text recognition. It provides a comprehensive reference for people entering this field, and could be helpful to inspire future research. Related resources are available at our Github repository: <https://github.com/HCIILAB/Scene-Text-Recognition>.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: scene text recognition, end-to-end systems, deep learning

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1 INTRODUCTION

Text is a system of symbols used to record, communicate, or inherit culture. As one of the most influential inventions of humanity, text has played an important role in human life. Specifically, rich and precise semantic information carried by text is important in a wide range of vision-based application scenarios, such as image search [179], intelligent inspection [19], industrial automation [63], robot navigation [38], and instant translation [124]. Therefore, text recognition in natural scenes has drawn the attention of researchers and practitioners, as indicated by the emergence of recent “ICDAR Robust Reading Competitions” [126], [125], [158], [83], [82], [156], [176].

Recognizing text in natural scenes, also known as scene text recognition (STR), is usually considered as a special form of optical character recognition (OCR), i.e., camera-based OCR. Although OCR in scanned documents is well developed [137], [241], STR remains challenging because of many factors, such as complex backgrounds, various fonts, and imperfect imaging conditions. Figure 1 compares the following characteristics of STR and OCR in scanned documents.

*Both authors contributed equally to this research.

Authors’ address: Xiaoxue Chen, xxuechen@foxmail.com; Lianwen Jin, lianwen.jin@gmail.com; Yuanzhi Zhu, z.yuanzhi@foxmail.com; Canjie Luo, canjie.luo@gmail.com; Tianwei Wang, wangtw@foxmail.com, the College of Electronic and Information Engineering, South China University of Technology, Guangzhou, China.

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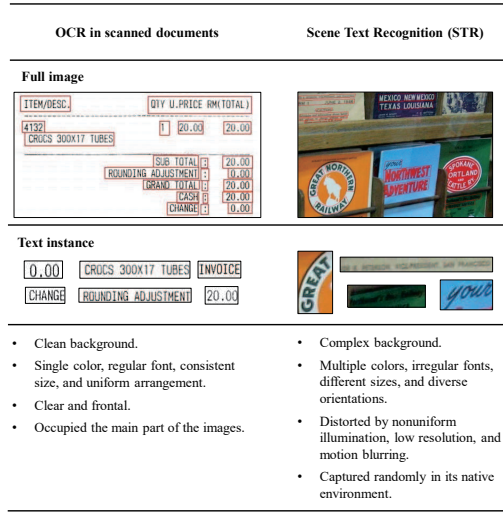


Fig. 1. Comparison of STR and OCR in scanned documents.

- **Background:** Unlike OCR in scanned documents, text in natural scenes can appear on anything (e.g., signboards, walls, or product packagings). Therefore, scene text images may contain very complex backgrounds. Moreover, the texture of the background can be visually similar to text, which causes additional challenges for recognition.
- **Form:** Text in scanned documents is usually printed in a single color with regular font, consistent size, and uniform arrangement. In natural scenes, text appears in multiple colors with irregular fonts, different sizes, and diverse orientations. The diversity of text makes STR more difficult and challenging than OCR in scanned documents.
- **Noise:** Text in natural scenes is usually distorted by noise interference, such as nonuniform illumination, low resolution, and motion blurring. Imperfect imaging conditions cause failures in STR.
- **Access:** Scanned text is usually frontal and occupies the main part of the image. However, scene text is captured randomly, which results in irregular deformations (such as perspective distortion). Various shapes of text increase the difficulty of recognizing characters and predicting text strings.

Recognizing text in natural scenes has attracted great interest from academia and industry in recent years because of its importance and challenges.

Early research [196], [141], [218] mainly relied on hand-crafted features. Low capabilities of these features limited the recognition performance. With the development of deep learning, neural networks significantly boosted the performance of STR. Several primary factors are driving deep learning-based STR algorithms. The first factor is the advances in hardware systems. High-performance computing systems [37] can train large-scale recognition networks. Moreover, modern mobile devices [21], [109] are capable of running complex algorithms in real-time. The second is automatic feature learning in deep learning-based STR algorithms, which not only frees researchers from the exhausting work of designing and selecting hand-crafted features, but also significantly improves recognition performance. The third is the growing demand for STR applications [32], [157],

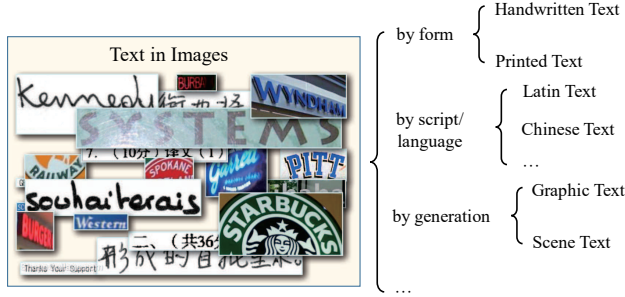


Fig. 2. Typical classifications of text in images.

[240], [224], [215]. Text in natural scenes can provide rich and precise information, which is beneficial for understanding the scene. Automatic recognition of text in natural scenes is economically viable in the era of big data, which attracts researchers and practitioners.

This paper attempts to comprehensively review the field of STR and establish a baseline for a fair comparison of algorithms. We present the entire picture of STR by summarizing fundamental problems and the state-of-the-art, introducing new insights and ideas, and looking ahead into future trends. Hence, this paper aims to serve as a reference for researchers and can be helpful in future work. Moreover, we provide a comprehensive review of publicly available resources, including the standard benchmark datasets and related code.

There are several STR reviews in the literature [236], [180], [222], [243], [228], [122]. However, most of the above-mentioned surveys [236], [180], [222], [243], [228] are outdated. Many recent advances, such as the algorithms developed in 2018 – 2020, are not included in these surveys. We refer the readers to these papers for a more comprehensive historical literature review. Moreover, Zhu et al. [243] and Long et al. [122] reviewed methods for both scene text detection and recognition. Yin et al. [228] surveyed algorithms for text detection, tracking, and recognition in video. Unlike these surveys, our paper mainly focuses on STR and aims to provide a more detailed and comprehensive overview of this field.

The remainder of this paper is organized as follows. Section 2 presents the background, fundamental problems, and special issues associated with text. Section 3 introduces new insights and ideas developed for STR in recent years. Section 4 summarizes the standard benchmark datasets and evaluation protocols and compares the performance of recognition algorithms. Finally, Section 5 concludes the paper and identifies potential directions for future work in STR.

2 BACKGROUND

To comprehensively understand the field of STR, we will describe the fundamental problems and special issues associated with text. Moreover, some representative applications of STR will be listed and analyzed in this section.

2.1 Text in Images

Text can appear differently in the images. Figure 2 shows examples and typical classifications. For example, if classified by the text form, handwritten text and printed text are two basic classes. Notably, classification methods may overlap. Handwritten text recognition is more challenging than printed text recognition because of various handwriting styles and character-touching problem [209], [238]. Depending on the scripts/languages, text in images may comprise different characters

such as Latin, Chinese, or Hindi. Text characteristics, such as text categories and the reading order, vary greatly in different languages. Following the definition in [222], text in images can also be divided into “graphic text” and “scene text”. The former refers to text that is digitally added as an overlay on videos or images. The latter refers to text on objects, captured in its native environment. Scene text has diverse styles and can appear on any surface, which makes it difficult to distinguish text from complex backgrounds.

Typically, most approaches summarized in this paper deals with printed Latin scene text.

2.2 Fundamental Problems and Special Issues with Text

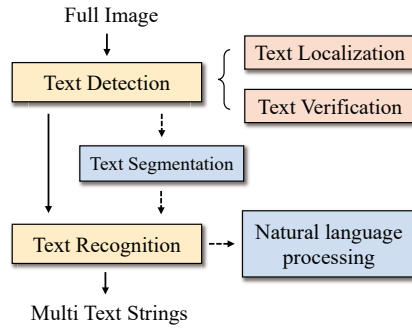


Fig. 3. Illustration of an end-to-end system, which defines various fundamental problems at various stages: text detection, text localization, text verification, text segmentation, and text recognition. Some stages are not considered in an end-to-end system.

Rich and precise information carried by text is important in many vision-based application scenarios. However, extracting text from natural scenes and using it in another application is a complex process. As illustrated in Figure 3, various fundamental problems were defined at various stages of this task in the literature: text localization, text verification, text detection, text segmentation, text recognition, and end-to-end systems. Moreover, special text-related issues exist because of the unique challenges of text. Text enhancement, text tracking, and natural language processing (NLP) are also briefly introduced. A clear understanding of these common concepts can help researchers to analyze the differences and connections between different tasks.

2.2.1 Fundamental Problems.

- **Text localization:** The objective of text localization [102] is to localize text components precisely and to group them into candidate text regions with as little background as possible [222]. Early text localization methods are based on low-level features, such as color [92], [225], gradient [95], [169], stroke width transform [41], [136], maximally stable extremal regions (MSER) [140], [166], canny detector [17], [28], and connected component analysis [87], [145]. Most of current methods are based on deep neural networks [68], [233], [226].
- **Text verification:** Text verification [89] aims at verifying the text candidate regions as text or non-text. It is usually used after text localization to filter the candidate regions, because text localization sometimes introduces false positives. Approaches to text verification include prior knowledge [85], [95], [168], support vector machine (SVM) classifier [224], and conditional random fields (CRFs) [89]. Recent works [196], [81] used a convolution neural network (CNN) to improve text/non-text discrimination.

- **Text detection:** The function of text detection [219], [201] is to determine whether text is present using localization and verification procedures [222]. As a basis of an end-to-end system, it provides precise and compact text instance images for text recognition. Text detection approaches can be roughly categorized as regression-based methods [116], [119], [237], [5], [207] and instance segmentation-based methods [204], [64], [213], [117].
- **Text segmentation:** Text segmentation has been identified as one of the most challenging problems [184]. It includes text line segmentation [223], [168] and character segmentation [144], [167]. The former refers to splitting a region of multiple text lines into multiple sub-regions of single text lines. The latter refers to separating a text instance into multiple regions of single characters. Character segmentation was typically used in early text recognition approaches [190], [132], [12].
- **Text recognition:** Text recognition [190] translates a cropped text instance image into a target string sequence. It is an important component of an end-to-end system, which provides credible recognition results. Traditional text recognition methods rely on hand-crafted features, such as histogram of oriented gradients descriptors [196], connected components [141], and stroke width transform [218]. Most recent studies have used deep learning encoder-decoder frameworks [24], [127], [163].
- **End-to-end system:** Given a scene text image, an end-to-end system [190] can directly convert all text regions into the target string sequences. It usually includes text detection [214], text recognition [161], and postprocessing. The construction of a real-time and efficient end-to-end systems [141], [12], [93] has become a new trend in recent years. Some researchers [190], [196], [2] interpret text detection and text recognition as two independent subproblems, which are combined to construct an end-to-end system. Another approach [81], [15], [70], [115] is to jointly optimize text detection and text recognition by sharing information.

2.2.2 *Special Issues.*

- **Script identification:** Script identification [22] aims to predict the script of a given text image. It plays an increasingly important role in multilingual systems. Detecting the script and language helps text recognition to select the correct language model [181]. Script identification can be interpreted as an image classification problem, where discriminative representations are usually designed, such as mid-level features [172], [160], convolutional features [51], [165], [130], and stroke-parts representations [52].
- **Text enhancement:** Text enhancement [10] can recover degraded text, improve text resolution [200], remove the distortions of text, or remove the background [128], which reduces the difficulty of text recognition. Many algorithms have been investigated for text enhancement and achieved promising results, such as the deconvolution [212], [16], learning-based methods [10], and sparse reconstruction [221].
- **Text tracking:** The purpose of text tracking [228], [178] is to maintain the integrity of text location and track text across adjacent frames in the video. Unlike static text in an image, tracking algorithms for moving text must identify precise text region at pixel level or sub-pixel level, because false tracking may blend text with its background or noise text. Spatial-temporal analysis [239], [113] is usually used for text tracking in the video. A recent study [155] also predicts movement to track characters.
- **Natural language processing:** Natural language processing (NLP) [30] explores how to use computers to understand and manipulate natural language text or speech. NLP is a bridge for human-computer communication. Text, as the most important type of unstructured data, is the main object of NLP. There is a wide range of text-based applications of NLP, including

machine translation [6], [23], automatic summarization [232], [105], question answering [3], [36], and relationship extraction [211], [96].

2.3 Applications

Text, as the most important carrier of communication and perception of the world, enriches our lives. Numerous applications of scene text recognition across various industries and in our daily life: i) Intelligent transportation. Constructing automatic geocoding systems [157], [206] is not only convenient to travel, but also enables users to overcome language barriers, e.g., automatically recognizing the road signs [21] and translating text into another language. ii) Information extraction. Although text in the pictures contains precise information, it is almost impossible to type-in massive data by human alone in the era of big data. For example, the number of China's express delivery business has exceeded 40 billion [75] in 2017. Automatically recognizing text in natural scenes can save huge resources as well as protect customer privacy. iii) Visual input and access. According to the World Health Organization¹, at least 2.2 billion people live in the world with a vision impairment or blindness. In addition to advanced medical methods, scene text recognition technology can also improve their life, e.g., developing text-to-speech devices to help understand books, ATM instructions and pharmaceutical labels [42]. Apart from the applications we have mentioned above, there have been some specific STR application scenarios, such as text visual question answering (text VQA) [171], [13], e-discovery [9], multimedia retrieval [240], [224], automatic identity authentication, which are also quietly changing our life quality.

3 METHODOLOGIES

In early research, hand-crafted features were used for text recognition, such as histogram of oriented gradients descriptors [196], connected components [141], and stroke width transform [218]. However, the performances of these methods are limited by low-capacity features. With the rise and development of deep learning, the community has witnessed substantial advancements in innovation, practicality, and efficiency of various methods. Comparing with traditional methods, deep learning methods have the following advantages: i) Automation: automatic feature representation learning can free researchers from empirically designing the hand-crafted features. ii) Effectiveness: excellent recognition performance far exceeds traditional algorithms. iii) Generalization: algorithms can be easily applied to similar vision-based problems. In this section, we introduce new insights and ideas proposed for STR and end-to-end systems in the era of deep learning. The primary contribution of each approach is reviewed. In the case of multiple contributions, we analyze them separately.

3.1 Cropped Scene Text Image Recognition

The objective of STR is to translate a cropped text instance image into a target string sequence. There are two types of scene text in nature, i.e., regular and irregular. Two main STR categories exist: segmentation-based methods and segmentation-free methods. For segmentation-free methods, they can be roughly classified into CTC-based [57] methods [161] and attention-based [6] methods [163], [127]. Besides, other promising ideas are also introduced in this section, such as label embedding [1], [154]. Table 1 gives a comprehensive list and categorization of these recognition methods.

3.1.1 Segmentation-Based Methods. One category of STR approaches is based on segmentation [12], [196], [81], which usually includes three steps: image preprocessing, character segmentation, and character recognition. Segmentation-based methods attempt to locate the position of each

¹<https://www.who.int/health-topics/blindness-and-vision-loss>

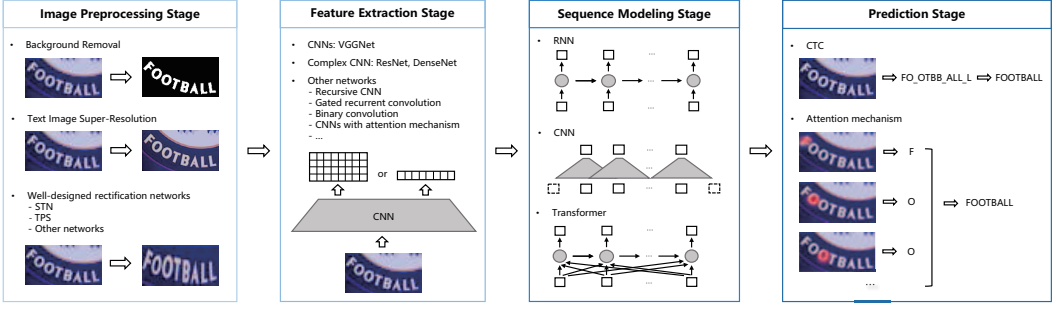


Fig. 4. Overview of segmentation-free STR approach. Image preprocessing and sequence modeling stages are not necessarily required. Moreover, elements of image preprocessing can be combined to further improve recognition performance.

character from the input text instance image, apply a character classifier to recognize each character, and group characters into text lines to obtain the final recognition results.

An early successful STR system based on deep learning was developed by Wang et al. [190], which used a pictorial model that took the scores and locations of characters as input to determine an optimal configuration of a particular word from a small lexicon. The proposed recognition algorithm outperformed a leading commercial OCR engine ABBYY FineReader², which is a baseline for STR. Later, inspired by the success of the deep convolutional neural network in visual understanding [90], Wang et al. [196], Mishra et al. [134], and Liu et al. [111] combined a multilayer neural network with unsupervised feature learning to train a highly-accurate character recognizer module. For postprocessing, the character responses with character spacings, the beam search algorithm [104] or the weighted finite state transducer [135] based representation were applied to recognize target words in a defined lexicon. To further improve recognition performance, researchers explored robust word image representations, such as scale invariant feature transform (SIFT) descriptors [152], Strokelets [220], and mid-level features [55].

All of the aforementioned methods rely on lexicons to obtain the final recognition results. However, the query time linearly depends on the size of the lexicon. With an open lexicon, these strategies are impractical because of the large search space. To address this issue, lexicon-free attempts had been made for STR. Some researchers [132] overcame the need for restricted word lists by adopting large dictionaries as higher-order statistical language models. Others solved STR in a lexicon-free manner by leveraging larger-scale data [12] and more complex neural networks [81], [61], e.g., convolutional Maxout network [54]. Recently, Wan et al. [185] built a recognition system based on semantic segmentation, which could predict the class and geometry information of characters with two separate branches and further improve recognition performance.

Although significant progress has been made in segmentation-based methods for STR, there are critical shortcomings: i) All these pipelines require accurate detection of individual characters, which has been identified as one of the most challenging problems in the community[184]. Therefore, the quality of character detectors/segmentors usually constrains the recognition performance. ii) Segmentation-based recognizers fail to model contextual information beyond individual characters, which may result in poor word-level results during the training.

3.1.2 Segmentation-Free Methods. The second category is segmentation-free methods [173], [161], [24], [163], [127]. The approach is to recognize the text line as a whole and focus on mapping the

²<http://finereader.abbyy.com>

Table 1. Summary of the existing recognition approaches. ‘SK’, ‘ST’, ‘ExPu’, ‘ExPr’, and ‘Un’ indicate the approaches that use Synth90K dataset, SynthText dataset, extra public data, extra private data, and unknown data, respectively. ‘Regular’ indicates the objective is regular datasets where most text instances are frontal and horizontal. ‘Irregular’ indicates the objective is irregular datasets where most of the text instances are low-resolution, perspective distorted, or curved. ‘**’ indicates the methods that use the extra datasets other than Synth90k and SynthText.

Method	Year	Data	Regular	Irregular	Segmentation	CTC	Attention	Source Code
Wang et al. [190] : ABBYY	2011	Un	✓	✗	✓	✗	✗	✗
Wang et al. [190] : SYNTH+PLEX	2011	ExPr	✓	✗	✓	✗	✗	✗
Mishra et al. [132]	2012	ExPu	✓	✗	✓	✗	✗	✗
Wang et al. [196]	2012	ExPr	✓	✗	✓	✗	✗	✗
Goel et al. [59] : wDTW	2013	Un	✓	✗	✓	✗	✗	✗
Bissacco et al. [12] : PhotoOCR	2013	ExPr	✓	✗	✓	✗	✗	✗
Phan et al. [152]	2013	ExPu	✗	✓	✓	✗	✗	✗
Alsharif et al. [2] : HMM/Maxout	2014	ExPu	✓	✓	✓	✗	✗	✗
Almazan et al. [1] : KCSR	2014	ExPu	✓	✗	✗	✗	✗	https://github.com/almazan/watts
Yao et al. [220] : Strokelets	2014	ExPu	✓	✗	✓	✗	✗	✗
R-Serrano et al. [154] : Label embedding	2015	ExPu	✓	✗	✓	✗	✗	✗
Jaderberg et al. [81]	2014	ExPu	✓	✗	✓	✗	✗	https://bitbucket.org/jaderberg/ecv2014_textspotting/src/master/
Su and Lu [173]	2014	ExPu	✓	✗	✓	✓	✗	✗
Gordo [55] : Mid-features	2015	ExPu	✓	✗	✓	✗	✗	✗
Jaderberg et al. [78]	2015	ExPr	✓	✗	✓	✗	✗	http://www.robots.ox.ac.uk/~vgg/research/text/
Jaderberg et al. [79]	2015	SK + ExPr	✓	✗	✓	✗	✗	✗
Shi, Bai, and Yao [161] : CRNN	2017	SK	✓	✗	✗	✓	✗	https://github.com/bgshih/crnn
Shi et al. [163] : RARE	2016	SK	✗	✓	✗	✗	✓	https://github.com/majieru/crnn_pytorch
Lee and Osindero [91] : R2AM	2016	SK	✓	✗	✗	✗	✓	✗
Liu et al. [108] : STAR-Net	2016	SK + ExPr	✓	✓	✓	✗	✓	✗
*Liu et al. [111]	2016	ExPu	✓	✗	✓	✗	✗	✗
*Mishra et al. [134]	2016	ExPu	✓	✗	✓	✗	✗	✗
*Su and Lu [174]	2017	SK + ExPu	✓	✗	✗	✓	✗	✗
*Yang et al. [217]	2017	ExPu	✗	✓	✗	✗	✓	✗
Yin et al. [227]	2017	SK	✓	✗	✗	✓	✗	✗
Wang et al. [189] : GRCNN	2017	SK	✓	✗	✗	✓	✗	https://github.com/jianfeng1991/GRCNN-for-OCR
*Cheng et al. [24] : FAN	2017	SK + ST (Pixel-level)	✓	✗	✗	✗	✓	✗
Cheng et al. [25] : AON	2018	SK + ST	✓	✓	✗	✗	✓	✗
Liu et al. [107] : Char-Net	2018	SK	✓	✗	✗	✗	✓	✗
*Liu et al. [121] : SqueezedText	2018	ExPr	✓	✗	✗	✗	✗	✗
*Zhan et al. [234]	2018	Pr(5 million)	✓	✗	✗	✓	✗	https://github.com/fnshun/Verisimilar-Image-Synthesis-for-Accurate-Detection-and-Recognition-of-Texts-in-Scenes
*Bai et al. [8] : EP	2018	SK + ST (Pixel-level)	✓	✗	✗	✗	✓	✗
Fang et al. [44]	2018	SK + ST	✓	✗	✗	✗	✓	https://github.com/FangShancheng/conv-ensemble-str
Liu et al. [106] : EnEsCTC	2018	SK	✓	✗	✗	✓	✗	https://github.com/liuhu-bige/enctc.cmn
Liu et al. [120]	2018	SK	✓	✗	✗	✓	✗	✗
Wang et al. [187] : MAAN	2018	SK	✓	✗	✗	✓	✗	✗
Sheng et al. [159] : NRTR	2018	SK	✓	✗	✗	✓	✓	✗
Gao et al. [47]	2018	SK	✓	✗	✗	✓	✓	✗
Shi et al. [163] : ASTER	2018	SK + ST	✗	✓	✗	✗	✓	https://github.com/bgshih/aster
Luo et al. [127] : MORAN	2019	SK + ST	✗	✓	✗	✗	✓	https://github.com/Canjie-Luo/MORAN_v2
Luo et al. ³ : MORAN-v2	2019	SK + ST	✗	✓	✗	✗	✓	https://github.com/Canjie-Luo/MORAN_v2
Chen et al. [20] : AEG	2019	SK + ST	✗	✓	✗	✗	✓	✗
Xie et al. [205] : CAN	2019	SK	✓	✗	✗	✗	✓	✗
*Liao et al. [101] : CA-FCN	2019	SK + ST + ExPr	✗	✓	✗	✗	✓	https://github.com/wangpengnoman/SAR-Strong-Baseline-for-Text-Recognition
*Li et al. [94] : SAR	2019	SK + ST + ExPr	✗	✓	✗	✗	✓	✗
Zhan et al. [233] : ESIR	2019	SK + ST	✓	✓	✗	✗	✓	✗
Zhang et al. [238] : SSDAN	2019	SK	✓	✗	✗	✗	✓	✗
*Yang et al. [216] : ScRN	2019	SK + ST(Char-level + Word-level)	✓	✗	✗	✗	✓	✗
*Yang et al. [192]	2019	SK + ST + ExPu	✓	✗	✗	✗	✓	✗
Wang et al. [195] : GCAM	2019	SK + ST	✓	✗	✗	✗	✓	✗
Jeonghun et al. [4]	2019	SK + ST	✓	✓	✗	✗	✓	https://github.com/clovaa/deep-text-recognition-benchmark
Huang et al. [76] : EPAN	2019	SK + ST	✓	✓	✗	✗	✓	✗
Gao et al. [48]	2019	SK	✓	✗	✗	✓	✗	✗
*Qi et al. [147] : CCL	2019	SK + ST(Char-level + Word-level)	✓	✗	✗	✓	✗	✗
*Wang et al. [193] : ReLFA	2019	ST(Char-level + Word-level)	✓	✗	✗	✗	✓	✗
*Zhu et al. [242] : HATN	2019	SK + Pu	✓	✓	✗	✗	✓	✗
*Zhan et al. [235] : SF-GAN	2019	Pr(1 million)	✓	✓	✗	✗	✓	✗
Liao et al. [98] : SAM	2019	SK + ST	✗	✓	✗	✗	✓	https://github.com/MhlLiao/MaskTextSpotter
*Liao et al. [98] : seg-SAM	2019	SK + ST (Char-level)	✗	✓	✗	✗	✓	https://github.com/MhlLiao/MaskTextSpotter
Wang et al. [197] : DAN	2020	SK + ST	✗	✓	✗	✗	✓	https://github.com/Wang-Tianwei/Decoupled-attention-network
Wang et al. [198]	2020	SK + ST	✗	✓	✗	✗	✓	https://github.com/xieenze/TextSR
*Wan et al. [185] : TextScanner	2020	SK + ST (Char-level)	✗	✓	✓	✗	✗	✗
*Hu et al. [73] : GTC	2020	SK + ST + ExPu	✗	✓	✗	✓	✓	✗
Luo et al. [128]	2020	SK + ST	✗	✓	✗	✗	✓	✗
*Litman et al. [103]	2020	SK + ST + ExPu	✗	✓	✗	✗	✓	✗
Yu et al. [229]	2020	SK + ST	✗	✓	✗	✗	✓	✗
Qiao et al. [149]	2020	SK + ST	✗	✓	✗	✗	✓	https://github.com/Pay20Y/SEED

entire text instance image into a target string sequence directly by a encoder-decoder framework, thus, avoiding character segmentation. Figure 4 shows a typical segmentation-free method, which contains the four stages of image preprocessing, feature representation, sequence modeling, and prediction.

Image Preprocessing Stage

Image preprocessing aims to improve the image quality by mitigating the interferences from imperfect imaging conditions, which may improve feature representation and recognition.

- **Background Removal.** Text may appear in various scenes with complex backgrounds. Texture features of backgrounds can be visually similar to the text, which causes additional difficulties in recognition.

Instead of complicated feature representations [120] and synthesis approaches [43], [203], an intuitive but rarely noticed solution is to separate the text content from complex backgrounds. Although traditional binarization methods [18] work well on document images, they fail to handle substantial variations in text appearance and noise in natural images. Recently, Luo et al. [128] used generative adversarial networks (GANs) [53] to remove the background while retaining the text contents, which reduced recognition difficulties and dramatically boosted performance.

- **Text Image Super-Resolution (TextSR).** Scene text is usually distorted by various noise interferences, such as low resolution. Low resolution can lead to misrecognized characters or words. Text image super-resolution (TextSR) [146] can output a plausible high-resolution image that is consistent with a given low-resolution image. This approach can help with text recognition in low-resolution images.

Classical approaches, such as bilinear, bicubic, or designed filtering, aim to reconstruct the detailed texture of natural images, but are not applicable to blurred text [198]. Instead of simply treating super-resolution as a regression problem [39], Wang et al. [198] first combined TextSR methods with recognition task, which significantly improved the performance of the text recognizer.

- **Rectification.** The function of rectification is to normalize the input text instance image, remove the distortion, and reduce the difficulty of irregular text recognition. Specifically, irregular text [217] refers to text with perspective distortion or arbitrary curving shape, which usually causes additional challenges in recognition.

The spatial transformer network (STN) [80] was used as an early rectification module to rectify the entire text image [162], [108] or individual character regions [107]. Later, Shi et al. [163] and Jeonghun et al. [4] adopted Thin-Plate-Spline (TPS) [202] to handle more complex distortions. Recently, some well-designed rectification networks were proposed. For example, a multi-object rectification network [127] was developed to rectify irregular text by predicting the offsets of each part of an input image. Zhan et al. [233] designed a novel line-fitting transformation and an iterative TPS-based rectification framework for optimal scene text rectification. Based on local attributes, such as center line, scale, and orientation, Yang et al. [216] proposed a symmetry-constrained rectification network.

To handle a variety of distortions, complex rectification modules are required and become a new trend. However, these affect the speed and memory consumption of recognition algorithms. Practitioners should choose the best trade-offs depending on their needs under different application scenarios. Moreover, with the development of irregular text detection, it is worth reconsidering whether a rectification module is required for a STR system.

Image preprocessing includes but is not limited to the aforementioned types. It can significantly reduce the difficulties of recognition by improving image quality. Various methods can be used in combination. Although many recognition algorithms exist, these auxiliary preprocessing approaches for text are not often used in the community, especially for background removal and TextSR. Moreover, most general off-the-shelf algorithms focus on the style of a single object, whereas scene text images usually contain multiple characters. Therefore, elaborate and dedicated-design preprocessing algorithms for STR deserve the attention of researchers in future work.

Feature Representation Stage

Feature representation maps the input text instance image to a representation that reflects the attributes relevant for character recognition, while suppressing irrelevant features such as font, color, size, and background.

Motivated by the successes of [191], [133], [190], Su et al. [173] used the histogram of oriented gradients (HOG) feature [34] in their STR system to construct sequential features of word images. Later, CNNs [227], [25], [107], [234], [127] have been widely used for feature representation stage, such as the VGGNet [170], [161], [162], [79], [24], [217], [193]. For more powerful feature representation, some complex neural networks were applied in STR algorithms, such as ResNet [66] [108], [44], [187], [163], [20], [197], [205], [94], [233], [216], [195], [4], [147], [242], [235] and DenseNet [74], [47], [48]. Recently, some attempts have been made to improve the feature representation module from different perspectives. Recursive CNNs were used by Lee et al. [91] for parametrically efficient and effective image feature representation, which can increase the depth of traditional CNNs under the same parametric capacity and produce much more compact feature response. Inspired by the recurrent convolution neural network (RCNN) in image classification [97], Wang et al. [189] designed a gated recurrent convolution layer for feature sequence representation by introducing a gate to control the context modulation in RCNN. Liu et al. [121] focused on real-time STR and proposed a novel binary convolutional layer. They claimed that the binary representation remarkably speeds up run-time inference and reduces memory usage. Some researchers [47], [238], [76], [48], [98], [44] argued that directly processing the source image by CNNs would introduce extra noise. Therefore, they combined CNNs with the attention mechanism [6] to enhance the representation of foreground text and suppress background noise.

A deeper and more advanced feature extractor usually results in a better representation power, which is suitable for improving STR with complex backgrounds. However, the performance improvement comes at the cost of memory and computation consumption [4]. A combination of the background removal technique [40] with simple feature extractors may be an alternative in future research.

Sequence Modeling Stage

Sequence modeling, as a bridge between visual features and predictions, can capture the contextual information within a sequence of characters for the next stage to predict each character, which is more stable and helpful than treating each symbol independently.

Multiple bidirectional long short term memory (BiLSTM) model was introduced in [59] and widely used in [173], [161], [162], [108], [174], [189], [25], [107], [187], [47], [163], [127], [20], [94], [233], [216], [195], [4], [193], [197] as the sequence modeling module because of its ability to capture long-range dependencies. Litman et al. [103] added intermediate supervisions along the network layers and successfully trained a deeper BiLSTM model to improve the encoding of contextual dependencies. However, some researchers [227], [44], [205], [48], [147] considered that BiLSTM was not an essential part of STR algorithms. They argued that although the BiLSTM was effective to model the context, its structure was computationally intensive and time consuming. Moreover, it could cause gradient vanishing/exploding during the training. Therefore, a sliding window [227] or deep one-dimensional CNN [44], [205], [48] was used instead of BiLSTM. In particular, although CNNs were widely used for feature extraction of individual characters in early research [196], [134], [111], the context can also be modeled by CNNs by precisely controlling the receptive field. Recently, Yu et al. [229] and Qiao et al. [149] focused on introducing global semantic information to model the context. Therefore, Yu et al. [229] designed a global semantic reasoning module to capture global semantic context through multi-way parallel transmission, while Qiao et al. [149] predicted an additional global semantic information supervised by the word embedding from a pre-trained language model.

Contextual cues are beneficial for image-based sequence recognition. Although recurrent neural networks (RNNs) [72] based structures, such as BiLSTM or LSTM, can model character sequences, there are some inherent limitations. In contrast, CNNs or transformer [182] can not only effectively deal with long sequences, but also be parallelized efficiently. Modeling language sequences using CNNs or transformer structure may be a new trend for sequence modeling because of its intrinsic superiority.

Prediction Stage

The objective of the prediction stage is to estimate the target string sequence from the identified features of the input text instance image. Connectionist temporal classification (CTC) [57] and the attention mechanism [6] are two major techniques. Moreover, other potential ideas regarding the prediction stage are also introduced in this section.

Connectionist Temporal Classification CTC was proposed by Graves et al. [57] for training RNNs [29], [72] to label unsegmented sequences directly. CTC has achieved significant improvements in many fields, such as speech recognition [60], [58] and online handwritten text recognition [59], [56]. CTC is typically used in STR as a prediction module, i.e., the transcription layer that converts the input features made by CNNs or RNNs into a target string sequence by calculating the conditional probability. In particular, CTC can maximize the likelihood of an output sequence by efficiently summing over all possible input-output sequence alignments, and allow the classifier to be trained without any prior alignment between the input and target sequences.

The formulation of the conditional probability can be briefly described as follows. The input features are denoted by $y = (y_1, y_2 \dots y_T)$, where T is the sequence length. Each y_t is a probability distribution over \mathcal{L} . Specifically, \mathcal{L} represents a set of all labels, including all characters and an extra blank symbol that represents an invalid output. A CTC path π is a sequence of length T , which consists of the blank symbol and label indices. As there are many possible ways to map these paths to transcription l , a CTC mapping function \mathcal{B} is defined to remove repeated labels and delete the blank symbol from each path. Then, the conditional probability is calculated by summing the probabilities of all paths mapped onto l by \mathcal{B} :

$$p(l|y) = \sum_{\pi: \mathcal{B}(\pi)=l} p(\pi|y), \quad (1)$$

where the probability of π is defined as $p(\pi|y) = \prod_{t=1}^T y_{\pi_t}^t$, and $y_{\pi_t}^t$ is the probability of having label π_t at time step t . As directly computing the above equation is computationally expensive, most researchers [108], [161], [227] adapt the forward-backward algorithm [59] to compute it efficiently.

Inspired by the success of CTC in speech processing, Su et al. [173], He et al. [69] and Shi et al. [161] first applied it to STR. Since then, numerous CTC-based prediction algorithms [108], [174], [227], [189], [47], [48], [147] have showed promising transcription performance. However, Liu et al. [106] argued that CTC tended to produce highly peaky and overconfident distributions, which was a symptom of over-fitting. To address this issue, they proposed a regularization method based on maximum conditional entropy to enhance generalization and exploration capabilities of CTC. Feng et al. [46] modified the traditional CTC by fusing focal loss to solve the recognition of extremely unbalanced samples. Recently, Hu et al. [73] improved the accuracy and robustness of CTC by using graph convolutional networks (GCNs) [86] in STR.

CTC enjoys remarkable transcription performance and stability. However, it faces some inherent limitations: i) The underlying methodology of CTC is sophisticated, which results in a large computational cost for long text sequences. ii) CTC suffers from the peaky distribution problems [57], [131] and its performance usually degrades for repeated patterns. iii) CTC can hardly be applied to two-dimensional (2D) prediction problems, such as irregular scene text recognition, where characters in the input text instance image are distributed in a spatial structure. To handle

this issue, Wan et al. [186] extended the vanilla CTC by adding another dimension along the height direction. Although the recognition performance is improved to some extent, the proposed 2D-CTC model has not completely solved 2D prediction problems. Therefore, applying CTC to solve the 2D prediction problem could be a potential direction for future research.

Attention Mechanism The attention mechanism was proposed by Bahdanau et al. [6] in the field of neural machine translation, which can automatically search for the predicted word that are relevant to parts of a given source sentence. Many approaches based on the attention mechanism have achieved significant improvements in various fields, such as image caption [71], text recognition [163], and scene classification of remote sensing images [194]. For STR, the attention mechanism is often combined with the RNN structure as a prediction module.

In particular, the attention mechanism learns the alignment between the input instance image and the output text sequences by referring to the history of the target characters and the encoded feature vectors. Let the output prediction sequence be denoted as $o = (o_1, o_2 \dots o_M)$, where M indicates the maximum decoding step size. At the t -th step, the output prediction o_t is given by:

$$o_t = \text{Softmax}(W_o s_t + b_o), \quad (2)$$

where s_t is the hidden state of RNN at time step t . Typically, a gated recurrent unit (GRU) [29] is used to update s_t and model the longterm dependencies. Hence, s_t is computed as

$$s_t = \text{GRU}(o_{prev}, g_t, s_{t-1}), \quad (3)$$

where o_{prev} is the embedding vector of the previous output o_{t-1} . Moreover, g_t represents the *glimpse vector*, computing as the weighted sum of features $h = (h_1, h_2 \dots h_N)$

$$g_t = \sum_{j=1}^N \alpha_{t,j} h_j, \quad (4)$$

where N is the feature length. Here, α_t is the vector of attention weights, which is computed as follows:

$$\alpha_{t,j} = \frac{\exp(e_{t,j})}{\sum_{i=1}^N \exp(e_{t,i})}, \quad (5)$$

$$e_{t,j} = \text{Tanh}(W_s s_{t-1} + W_h h_j + b), \quad (6)$$

where $e_{t,j}$ is the alignment score which represents the degree of correlation between the high-level feature representation and the current output. In the above Equations 2 – 6, W_o , b_o , W_s , W_h , and b are all trainable parameters.

Inspired by the development of neural machine translation systems, a large number of attention-based methods [91], [162], [217], [25], [163], [127], [94], [233], [238], [216], [4], [235] have emerged in STR field. Moreover, some attempts have been made to improve the vanilla attention from different perspectives: i) **Applying to 2D prediction problems.** For the irregular scene text recognition, the various character placements significantly increase the difficulty of recognition. The vanilla attention [91] was applied to perform 1D feature selection and decoding. There is the significant conflict between 2D text distribution and 1D feature representation by applying the vanilla attention directly. Therefore, Yang et al. [217], Li et al. [94], and Huang et al. [76] proposed 2D attention mechanism for irregular text recognition. ii) **Improving the construction of implicit language model.** Chen et al. [20] and Wang et al. [187] argued that the generated glimpse vector was not powerful enough to represent the predicted characters. Therefore, Chen et al. [20] introduced high-order character language models to the vanilla attention, while Wang et al. [187] constructed a memory-augmented attention model by feeding a part of the character sequence already generated and the all attended alignment history. Shi et al. [163] noted that a vanilla attention-based prediction module captured output dependencies in only one direction and

missed the other. Thus, they proposed a bidirectional attention-based decoder, with two decoders in opposite directions. iii) **Improving parallelization and reducing complexity.** Although the vanilla attention mechanism based on the RNN structure can capture long-range dependencies, it is computationally intensive and time consuming. A recent attention variant, namely Transformer [182], was widely employed in [242], [192], [159], [229] to improve parallelization and reduce complexity for STR. iv) **Addressing attention drift.** The *attention drift* phenomenon means that attention models cannot accurately associate each feature vector with the corresponding target region in the input image. Some researchers added extra information to solve this problem by focusing the deviated attention back onto the target areas, such as localization supervision [24] and encoded coordinates [193]. Others [195], [76], [242] increased the alignment precision of attention in a cascade way. Specifically, Wang et al. [197] argued that a serious alignment problem is caused by its recurrence alignment mechanism. Therefore, they decoupled the alignment operation from using historical decoding results.

In recent years, the attention-based prediction approaches have become the mainstream method in the field of STR and have outperformed CTC in decoding because of its ability to focus on informative areas. Moreover, the attentional methods can be easily extended to complex 2D prediction problems. However, the attention mechanism has some shortcomings: i) As this method relies on the attention module for label alignment, it requires more storage and computations [14]. ii) For long text sequences, the attention mechanism is difficult to train from scratch owing to the misalignment between the input instance image and the output text sequences [7], i.e., the attention drift phenomenon. iii) The current research of attention mechanism mainly focuses on languages which involve only a few character categories (e.g., English, French). To the best of our best knowledge, there is no public report on effectively applying the attention mechanism to deal with the large-scale category text recognition tasks, such as Chinese text recognition.

Discussion Both CTC and the attention mechanism have their strengths and limitations. Recently, some researchers [73], [103] applied both CTC and the attention mechanism to achieve accurate prediction and maintain a fast inference speed. Cong et al. [31] comprehensively compared these two prediction approaches on large-scale real-world scene text sentence recognition tasks. Based on extensive experiments, they provided practical advice for researchers and practitioners. For example, the attention-based approaches can achieve higher recognition accuracy on isolated word recognition tasks but perform worse on sentence recognition tasks compared with CTC-based approaches. Therefore, the right prediction methods should be chosen according to different application scenarios and constraints. Moreover, it is valuable to explore alternative prediction strategies in future work. For example, the aggregation cross-entropy function [208] was designed to replace CTC and the attention mechanism; it achieves competitive performance with a much quicker implementation, reduced storage requirements, and convenient employment.

3.1.3 Other Potential Approaches. Other approaches have been considered and explored with a different view. Motivated by “the whole is greater than the sum of parts,” Goel et al. [50] recognized text in natural scenes by matching the scene and synthetic image features with weighted dynamic time warping (wDTW) approach. Later, Almazán et al. [1] and Rodriguez et al. [154] interpreted the task of recognition and retrieval as a nearest neighbor problem. They embedded both word images and text strings in a common vectorial subspace or Euclidean space, combining label embedding with attributes learning. Specifically, images and strings that represent the same word would be close together. Recently, Jaderberg et al. [78] formulated STR as a multi-class classification problem. They trained a deep CNN-classifier solely on synthetic data: approximately 9 million images from a 90k words dictionary. As each word corresponds to an output neuron, the proposed text classifier

cannot recognize out-of-dictionary words. Further, they combined CNNs with a CRF graphical model for unconstrained text recognition [79].

Table 2. Summary of the existing end-to-end system approaches.

Method	Year	Detection	Recognition	Source Code
Wang et al. [190]	2011	Sliding windows and Random Ferns	Pictorial Structures	✗
Wang et al. [196]	2012	CNN-based	Sliding windows for classification	✗
Jaderberg et al. [81]	2014	CNN-based and saliency maps	CNN classifier	✗
Alsharif et al. [2]	2014	CNN and hybrid HMM Maxout models	Segmentation-based	✗
Yao et al. [218]	2014	Random Forest	Component Linking and Word Partition	✗
Neumann et al. [143]	2015	Extremal Regions	Clustering algorithm to group characters	✗
Jaderberg et al. [78]	2016	Region proposal mechanism	Word-level classification	✗
Liao et al. [100] : TextBoxes	2017	SSD-based framework	CRNN	https://github.com/MhLiao/TextBoxes
Büsta et al. [15] : Deep TextSpotter	2017	Yolo-v2	CTC	✗
Li et al. [93]	2017	Text Proposal Network	Attention	✗
Lyu et al. [129] : Mask TextSpotter	2018	Fast R-CNN with mask branch	Character segmentation	https://github.com/vpengyuan/masktextspotter.caffe2
He et al. [70]	2018	EAST framework	Attention	https://github.com/tonghe90/textspotter
Liu et al. [112] : FOTS	2018	EAST framework	CTC	https://github.com/jiangxiluning/FOTS.PyTorch
Liao et al. [99] : TextBoxes++	2018	SSD-based framework	CRNN	https://github.com/MhLiao/TextBoxes_plusplus
Liao et al. [98] : Mask TextSpotter	2019	Mask RCNN	Character segmentation, Spatial Attention Module	https://github.com/MhLiao/MaskTextSpotter
Xing et al. [210] : CharNet	2019	EAST framework	CNN classifier	https://github.com/MalongTech/research-charnet
Feng et al. [45] : TextDragon	2019	TextSnake	Sliding convolution character models with CTC	✗
Qin et al. [150]	2019	Mask RCNN	Attention	✗
Wang et al. [188] : Boundary	2020	RPN-based framework	Attention	✗
Qiao et al. [148] : Text Perceptron	2020	ResNet and Feature Pyramid Network	Attention	✗
Liu et al. [115] : ABCNet	2020	Bezier curve detection	CTC	https://github.com/Yuliang-Liu/bezier_curve_text_spotting

3.2 End-to-End Systems

Given a text image with a complex background as input, an end-to-end system aims to directly convert all text regions into string sequences. Typically, it includes text detection, text recognition, and postprocessing. In the past, text detection and recognition have been interpreted as two independent subproblems that are combined to retrieve text from images [190], [196], [81], [142], [62], [2], [78], [143], [100]. Recently, the construction of real-time and efficient end-to-end systems has become a new trend in the community. Table 2 compares the characteristics of these end-to-end methods.

Several factors promote the emergence of end-to-end systems: i) Errors can accumulate in a cascade way of text detection and recognition, which may lead to a large fraction of garbage predictions, while an end-to-end system can prevent errors from being accumulated during the training. ii) In an end-to-end system, text detection and recognition can share information and can be jointly optimized to improve overall performance. iii) An end-to-end system is easier to maintain and adapt to new domains, whereas maintaining a cascaded pipeline with data and model dependencies requires substantial engineering efforts. iv) An end-to-end system exhibits competitive performance with faster inference and smaller storage requirements.

Many recent studies [15] have shown the effectiveness of a joint optimized end-to-end model, which usually includes a detection branch and a recognition branch. Bartz et al. [11] integrated and jointly learned a STN [80] to detect text regions of an image. Corresponding image regions were directly cropped and fed into a simple neural network to recognize text content. Advanced detection [33], [177] and recognition algorithms [161] were then used to build joint end-to-end systems. Both branches were bridged by cropping region of interests (RoIs) features of the detection branch and feeding them to the recognition branch. Typically, RoIPool was proposed by Girshick [49] to convert RoIs of different scales and aspect ratios into fixed-size feature maps for object detection. However, this approach may lead to significant distortion because of the large variation of text length. To address this issue, Li et al. [93] proposed varying-size RoIPool to accommodate the original aspect ratios. As quantizations performed by RoIPool would introduce misalignments between the RoIs and the extracted features, many methods used bilinear interpolation to extract text instance features, such as bilinear sampling [15], RoIRotate [112], and the text alignment layer [70]. Recent

end-to-end systems [129], [98], [45], [188], [148] have focused on curved text of arbitrary shapes. For example, Liao et al. [129] and their extended work [98] used RoIAlign [65] to preserve more accurate location information, retrieved each character as a generic object, and composed the final text with character-level annotations. Feng et al. [45] generated dense detection quadrangles and used the proposed RoISlide to transform features cropped from each quadrangle into rectified features. All text features were then fed into a CTC-based recognizer, making the framework free from character-level annotations. Instead of formulating the text detection branch as a bounding box extraction or instance segmentation task, Wang et al. [188] localized a set of points on the boundary and adopted TPS [202] transformation to flatten features of each text. Qiao et al. [148] proposed the shape transform module, which iteratively generated potential fiducial points and used TPS to transform the detected text regions into regular morphologies without extra parameters. Liu et al. [115] introduced parameterized Bezier curve to adaptively fit arbitrarily-shaped text and designed a novel BezierAlign layer to precisely calculate convolutional features of text instances in curved shapes. The purpose of the aforementioned bilinear interpolation methods is to rectify the features of irregular shapes into axis-aligned features for text recognizer, where the difference is the way of generating the sampling grid. However, Qin et al. [150] argued that the feature rectification was a key bottleneck in generalizing to irregular shaped text. They introduced RoI masking to filter out the neighboring text and the background, which made rectification unnecessary for the recognizer. Xing et al. [210] directly performed character detection and recognition on the full features without any RoI operations.

Although the current end-to-end systems work fairly well in many real-world scenarios, they contain limitations. The following difficulties should be considered: i) How to efficiently bridge and share information between text detection and recognition? ii) How to balance the significant differences in learning difficulty and convergence speed between text detection and recognition? iii) How to improve joint optimization? Moreover, a simple, compact, and powerful end-to-end system is yet to be developed.

4 EVALUATIONS AND PROTOCOLS

Diverse datasets and unified evaluation protocols bring new challenges and fair comparison to the community, respectively, but both are necessary to advance the field of STR. In this section, we examine the standard benchmark datasets and evaluation protocols. Table 4 and Table 5 compare the performance of the current advanced algorithms in STR and end-to-end systems.

4.1 Datasets

Several primary reasons justify the need for additional datasets: i) Most deep learning approaches are data-driven. Large-scale datasets are important and crucial to train a good text recognizer. ii) Advanced STR algorithms have been overused on previous datasets, indicating that more challenging aspects could be investigated. iii) New datasets usually represent potential directions for future work, such as lexicon-free text recognition, irregular text recognition, unsupervised or weakly supervised text recognition, and large-scale category text recognition.

Depending on the type of dataset collection, we divide the standard benchmark datasets into two categories: synthetic datasets and realistic datasets. In particular, realistic datasets include regular Latin datasets, irregular Latin datasets and multilingual datasets. Table 3 describes the panorama of these datasets, and Figures 5 – 8 show representative samples.

4.1.1 Synthetic Datasets. Most deep learning algorithms rely on sufficient data. However, the existing realistic datasets are relatively small for training a highly accurate scene text recognizer, because they only contain thousands of data samples. Moreover, manually collecting and annotating

large amount of real-world data will involve huge efforts and resources. Therefore, synthetic and artificial data generation has been a popular research topic [77], [62], [234], [123].

Table 3. Comparison of the benchmark datasets. ‘50’, ‘1k’, and ‘full’ are the lexicon sizes.

Datasets	Language	Images			Instances			Lexicon	Char-Level Label	Type	Source Code
		Total	Train	Test	Total	Train	Test				
Synth90k [77]	English	~9000000	-	-	~9000000	-	-	✗	✗	Regular	http://www.robots.ox.ac.uk/vgg/data/text/
SynthText [62]	English	~6000000	-	-	~6000000	-	-	✗	✓	Regular	https://github.com/ankush-me/SynthText
Verisimilar Synthesis [234]	English	-	-	-	~5000000	-	-	✗	✗	Regular	https://github.com/frizban/Verisimilar-Image-Synthesis-for-Accurate-Detection-and-Recognition-of-Texts-in-Scenes
UnrealText [123]	English	~600000	-	-	~12000000	-	-	✗	✓	Regular	https://yiohuo.github.io/UnrealText/
IIIT5K [132]	English	1120	380	740	5000	2000	3000	50 and 1k	✓	Regular	http://cvit.iiit.ac.in/research/projects/cvit-projects/the-iiit-5k-word-dataset
SVT [190], [191]	English	350	100	250	725	211	514	50	✗	Regular	http://vision.ucsd.edu/~kai/svt/
IC03 [126]	English	509	258	251	2268	1157	1111	50, 1k and full	✓	Regular	http://www.iapr-tc11.org/media/wiki/index.php?title=ICDAR_2003_Robust_Reading_Competitions
IC11 [158]	English	522	420	102	4501	3583	918	✗	✓	Regular	http://www.cvc.uab.es/icdar2011competition/1com-competition/1com-downloads
IC13 [83]	English	561	420	141	5003	3564	1439	✗	✓	Regular	http://dagdata.cvc.uab.es/
SVHN [139]	Digits	600000	573968	26032	600000	573968	26032	✗	✓	Regular	http://ufdl.stanford.edu/housenumbers/
SVT-P [152]	English	238	0	238	639	0	639	50 and full	✗	Irregular	https://pan.baidu.com/s/trhYUn1m08OZQEGUz9Nmrg
CUTE80 [153]	English	80	0	80	288	0	288	✗	✗	Irregular	http://cs-chan.com/downloads_CUTE80_dataset.html
IC15 [82]	English	1500	1000	500	6545	4468	2077	✗	✗	Irregular	http://rrc.cvc.uab.es/?ch=4&com=downloads
COCO-Text [185]	English	63686	43686	10000	145859	118309	27550	✗	✗	Irregular	https://vision.cornell.edu/se3/coco-text-2/
Total-Text [26]	English	1555	1255	300	11459	11166	293	✗	✗	Irregular	https://github.com/cs-chan/Total-Text-Dataset
RCWTW-17 [164]	Chinese/English	12514	11514	1000	-	-	-	✗	✗	Regular	http://rcw.vlabs.net/dataset/
MTWI [67]	Chinese/English	20000	10000	10000	290206	141476	148730	✗	✗	Regular	https://pan.baidu.com/s/1SUODaOhV7YOPkrn0xS6Aelist/path=%2F(prw:gc9v)
CTW [230]	Chinese/English	32285	25887	3269	1018402	812872	103519	✗	✓	Regular	https://ctwdataset.github.io/
SCUT-CTW1500 [231]	Chinese/English	1500	1000	500	10751	7683	3068	✗	✗	Irregular	https://github.com/Yuliang-Liu/Curve-Text-Detector
LSVT [176], [175]	Chinese/English	450000	30000	20000	-	-	-	✗	✗	Irregular	https://rrc.cvc.uab.es/?ch=16&com=downloads
ALT [27]	Chinese/English	10166	5603	4563	98455	58029	40426	✗	✗	Irregular	https://rrc.cvc.uab.es/?ch=14&com=downloads
RCCTS-25k [27]	Chinese/English	25000	20000	5000	119713	100924	10789	✗	✓	Irregular	https://rrc.cvc.uab.es/?ch=12&com=downloads
MLT [138]	Multilingual	20000	10000	10000	191639	89177	102462	✗	✗	Irregular	https://rrc.cvc.uab.es/?ch=15&com=downloads

- **Synth90k.** The Synth90k dataset [77] contains 9 million synthetic text instance images from a set of 90k common English words. Words are rendered onto natural images with random transformations and effects, such as random fonts, colors, blur, and noises. Synth90k dataset can emulate the distribution of scene text images and can be used instead of real-world data to train data-hungry deep learning algorithms. Besides, every image is annotated with a ground-truth word.
- **SynthText.** The SynthText dataset [62] contains 800,000 images with 6 million synthetic text instances. As in the generation of Synth90k dataset, the text sample is rendered using a randomly selected font and transformed according to the local surface orientation. Moreover, each image is annotated with a ground-truth word.
- **Verisimilar Synthesis.** The Verisimilar Synthesis dataset [234] contains 5 million synthetic text instance images. Given background images and source texts, a semantic map and a saliency map are first determined which are then combined to identify semantically sensible and apt locations for text embedding. The color, brightness, and orientation of the source texts are further determined adaptively according to the color, brightness, and contextual structures around the embedding locations within the background image.
- **UnrealText.** The UnrealText dataset [123] contains 600K synthetic images with 12 million cropped text instances. It is developed upon Unreal Engine 4 and the UnrealCV plugin [151]. Text instances are regarded as planar polygon meshes with text foregrounds loaded as texture. These meshes are placed in suitable positions in 3D world, and rendered together with the scene as a whole. The same font set from Google Fonts⁴ and the same text corpus, i.e., Newsgroup20, are used as SynthText does.

4.1.2 Realistic Datasets. Most of current realistic datasets contain only thousands of text instance images. Therefore, for STR, realistic datasets are typically used to evaluate recognition algorithms under real-world conditions. Subsequently, we will list and briefly describe the existing realistic datasets: regular Latin datasets, irregular Latin datasets, and multilingual datasets.

⁴<https://fonts.google.com/>



Fig. 7. Realistic sample images of irregular Latin text from SVT-P, CUTE80, IC15, COCO-Text and Total-Text datasets.

- **ICDAR 2011 (IC11).** The IC11 dataset [158] contains 485 images. This is an extension of the dataset used for the text locating competitions of ICDAR 2003.
- **ICDAR 2013 (IC13).** The IC13 dataset [83] contains 561 images: 420 for training and 141 for testing. It inherits data from the IC03 dataset and extends it with new images. Similar to IC03 dataset, the IC13 dataset contains 1,015 cropped text instance images after removing the words with non-alphanumeric characters. No lexicon is associated with IC13. Notably, 215 duplicate text instance images [4] exist between the IC03 training dataset and the IC13 testing dataset. Therefore, care should be taken regarding the overlapping data when evaluating a model on the IC13 testing data.
- **Street View House Number (SVHN).** The SVHN dataset [139] contains more than 600,000 digits of house numbers in natural scenes. It is obtained from a large number of street view images using a combination of automated algorithms and the Amazon Mechanical Turk (AMT) framework⁵. The SVHN dataset was typically used for scene digit recognition.

Irregular Latin Datasets

For the irregular benchmark datasets, most of the text instances are low-resolution, perspective distorted, or curved. Various fonts and distorted patterns of irregular text bring additional challenges in STR.

- **StreetViewText-Perspective (SVT-P).** The SVT-P dataset [152] contains 238 images with 639 cropped text instances. It is specifically designed to evaluate perspective distorted text recognition. It is built based on the original SVT dataset by selecting the images at the same address on Google Street View but with different view angles. Therefore, most text instances are heavily distorted by the non-frontal view angle. Moreover, each image is associated with a 50-word lexicon and a full-word lexicon.
- **CUTE80 (CUTE).** The CUTE dataset [153] contains 80 high-resolution images with 288 cropped text instances. It focuses on curved text recognition. Most images in CUTE have a complex background, perspective distortion, and poor resolution. No lexicon is associated with CUTE.
- **ICDAR 2015 (IC15).** The IC15 dataset [82] contains 1,500 images: 1,000 for training and 500 for testing. Specifically, it contains 2,077 cropped text instances, including more than

⁵<https://www.mturk.com/mturk/welcome>

200 irregular text samples. As text images were taken by Google Glasses without ensuring the image quality, most of the text is very small, blurred, and multi-oriented. No lexicon is provided.

- **COCO-Text.** The COCO-Text dataset [183] contains 63,686 images with 145,859 cropped text instances. It is the first large-scale dataset for text in natural images and also the first dataset to annotate scene text with attributes such as legibility and type of text. However, no lexicon is associated with COCO-Text.
- **Total-Text.** The Total-Text [26] contains 1,555 images with 11,459 cropped text instance images. It focuses on curved scene text recognition. Images in Total-Text have more than three different orientations, including horizontal, multi-oriented, and curved. No lexicon is associated with Total-Text.

Multilingual Datasets

Multilingual text can be found in modern cities, where representatives of multiple cultures live and communicate. Bilingual datasets are the simplest form. Subsequently, some bilingual or multilingual scene text datasets are introduced below. The bilingual datasets introduced in this paper are mainly composed of Latin and Chinese.

The reason for choosing Chinese as the second language of bilingual scene text datasets are three-fold. First, Chinese is one of the most widely used languages in the world. Second, although many STR algorithms exist, most of them focus on Latin characters. The problem of recognition of Chinese scene text has not been solved well. Third, Chinese text has unique characteristics compared with Latin text: i) Chinese is a large-scale category text, with a much larger character set than in Latin text. ii) The imbalanced class problem of Chinese characters is more obvious owing to the larger character set. iii) Many confusing characters with similar structures exist in Chinese, which makes them hard to distinguish. Therefore, reading Chinese in the wild is an important and challenging problem.

- **Reading Chinese Text in the Wild (RCTW-17).** The RCTW-17 dataset [164] contains 12,514 images: 11,514 for training and 1,000 for testing. Most are natural images collected by cameras or mobile phones, whereas others are digital-born. Text instances are annotated with labels, fonts, languages, etc.
- **Multi-Type Web Images (MTWI).** The MTWI dataset [67] contains 20,000 images. This is the first dataset constructed by Chinese and Latin web text. Most images in MTWI have a relatively high resolution and cover diverse types of web text, including multi-oriented text, tightly-stacked text, and complex-shaped text.
- **Chinese Text in the Wild (CTW).** The CTW dataset [230] includes 32,285 high-resolution street view images with 1,018,402 character instances. All images have character-level annotations: the underlying character, the bounding box, and six other attributes.
- **SCUT-CTW1500.** The SCUT-CTW1500 dataset [231] contains 1,500 images: 1,000 for training and 500 for testing. In particular, it provides 10,751 cropped text instance images, including 3,530 with curved text. The images are manually harvested from the Internet, image libraries such as Google Open-Image [88], or phone cameras. The dataset contains a lot of horizontal and multi-oriented text.
- **Large-Scale Street View Text (LSVT).** The LSVT dataset [176], [175] contains 20,000 testing samples, 30,000 fully annotated training samples, and 400,000 training samples with weak annotations (i.e., with partial labels). All images are captured from streets and reflect a large variety of complicated real-world scenarios, e.g., store fronts and landmarks.
- **Arbitrary-Shaped Text (ArT).** The ArT dataset [27] contains 10,166 images: 5,603 for training and 4,563 for testing. ArT is a combination of Total-Text, SCUT-CTW1500, and Baidu



Fig. 8. Realistic sample images of multilingual scene text from RCTW-17, MTWI, CTW, SCUT-CTW1500, LSVT, ArT, ReCTS-25k, and MLT datasets.

Curved Scene Text⁶, which was collected to introduce the arbitrary-shaped text problem. Moreover, all existing text shapes (i.e., horizontal, multi-oriented, and curved) have multiple occurrences in the ArT dataset.

- **Reading Chinese Text on Signboard (ReCTS-25k).** The ReCTS-25k dataset [114] contains 25,000 images: 20,000 for training and 5,000 for testing. All the text lines and characters are annotated with locations and transcriptions. All the images are from the Meituan-Dianping Group, collected by Meituan business merchants, using phone cameras under uncontrolled conditions. Specifically, ReCTS-25k dataset mainly contains images of Chinese text on signboards.
- **Multi-lingual Text (MLT-2019).** The MLT-2019 dataset [138] contains 20,000 images: 10,000 for training (1,000 per language) and 10,000 for testing. The dataset includes ten languages, representing seven different scripts: Arabic, Bangla, Chinese, Devanagari, English, French, German, Italian, Japanese, and Korean. The number of images per script is equal.

⁶A subset of LSVT

4.2 Evaluation Protocols

In this section, we summarize the evaluation protocols for Latin text and multilingual text.

4.2.1 Evaluation Protocols for Latin Text. **Recognition Protocols**

The word recognition accuracy (*WRA*) and word error rate (*WER*) are two widely used recognition evaluation protocols for Latin text.

- **WRA.** *WRA* is defined by

$$WRA = \frac{W_r}{W}, \quad (7)$$

where W is the total number of words, and W_r represents the number of correctly recognized words.

- **WER.** *WER* is defined by

$$WER = 1 - WRA = 1 - \frac{W_r}{W}. \quad (8)$$

End-to-End Protocols

Widely used evaluation protocols for Latin end-to-end systems⁷ are defined in [83], [82], where the recognition algorithms are evaluated in two modalities: *end-to-end recognition* and *word spotting*. In particular, all words in the scene text images should be detected and recognized under *end-to-end recognition*. Under *word spotting*, only words provided in the vocabulary should be detected and recognized. Moreover, three different vocabularies are provided for candidate transcriptions: *strongly contextualised*, *weakly contextualised* and *generic* (denoted as **S**, **W**, and **G** in short, respectively).

- **Strongly Contextualised (S).** The per-image vocabulary consists of 100 words, including all words in the corresponding image as well as distractors selected from the rest of the training/testing set, which follows the setup of [190].
- **Weakly Contextualised (W).** The vocabulary includes all words in the training/testing set.
- **Generic (G).** The generic vocabulary contains approximately 90K words derived from the dataset⁸ of Jaderberg et al. [78].

4.2.2 Evaluation Protocols for Multilingual Text. In this section, we briefly introduce the evaluation protocols for multilingual text widely used in recent competitions, such as *RCTW* [164], *MTWI* [67], *LSVT* [176], *ArT* [27], *ReCTS* [114], and *MLT* [138] competitions.

Recognition Protocols

Most competitions [67], [27], [114] measured the algorithm recognition performance by a traditional evaluation metric — the *normalized edit distance (NED)*:

$$NED = \frac{1}{N} \sum_{i=1}^N D(s_i, \hat{s}_i) / \max(l_i, \hat{l}_i), \quad (9)$$

where $D(\cdot)$ stands for the Levenshtein distance. s_i and \hat{s}_i denote the predicted text and the corresponding ground truth, respectively. Furthermore, l_i and \hat{l}_i are their text length. N is the total number of text lines. The *NED* protocol measures the mis-matching between the predicted text and the corresponding ground truth. Therefore, the recognition score is usually calculated as $1 - NED$.

End-to-End Protocols

Two main evaluation protocols for end-to-end systems have been used during recent competitions:

⁷https://rrc.cvc.uab.es/files/Robust_Reading_2015_v02.pdf

⁸Available at: <http://www.robots.ox.ac.uk/~vgg/ldataltext/>

Table 4. Performance comparison of recognition algorithms on benchmark datasets. ‘50’, ‘1k’, and ‘Full’ are lexicon sizes. ‘None’ means lexicon-free. ‘**’ indicates the methods that use the extra datasets other than Synth90k and SynthText. The **bold** represents the best recognition results. ‘†’ denotes the best recognition performance of using extra datasets.

Method	IIT5K			SVT		IC03				IC13		SVT-P			CUTE80	IC15	COCO-TEXT
	50	1K	None	50	None	50	Full	50k	None	None	None	50	Full	None	None	None	None
Wang et al. [190] : ABBYY	24.3	-	-	35.0	-	56.0	55.0	-	-	-	-	40.5	26.1	-	-	-	-
Wang et al. [190] : SYNTH+PLEX	-	-	-	57.0	-	76.0	62.0	-	-	-	-	-	-	-	-	-	-
Mishra et al. [132]	64.1	57.5	-	73.2	-	81.8	67.8	-	-	-	-	45.7	24.7	-	-	-	-
Wang et al. [196]	-	-	-	70.0	-	90.0	84.0	-	-	-	-	40.2	32.4	-	-	-	-
Goel et al. [50] : wDTW	-	-	-	77.3	-	89.7	-	-	-	-	-	-	-	-	-	-	-
Bissacco et al. [12] : PhotoOCR	-	-	-	90.4	78.0	-	-	-	-	-	87.6	-	-	-	-	-	-
Phan et al. [152]	-	-	-	73.7	-	82.2	-	-	-	-	-	62.3	42.2	-	-	-	-
Alsharif et al. [2] : HMM/Maxout	-	-	-	74.3	-	93.1	88.6	85.1	-	-	-	-	-	-	-	-	-
Almazan et al. [1] : KCSR	88.6	75.6	-	87.0	-	-	-	-	-	-	-	-	-	-	-	-	-
Yao et al. [220] : Strokelets	80.2	69.3	-	75.9	-	88.5	80.3	-	-	-	-	-	-	-	-	-	-
R-Serrano et al. [154] : Label embedding	76.1	57.4	-	70.0	-	-	-	-	-	-	-	-	-	-	-	-	-
Jaderberg et al. [81]	-	-	-	86.1	-	96.2	91.5	-	-	-	-	-	-	-	-	-	-
Su and Lu [173]	-	-	-	83.0	-	92.0	82.0	-	-	-	-	-	-	-	-	-	-
Gordo [55] : Mid-features	93.3	86.6	-	91.8	-	-	-	-	-	-	-	-	-	-	-	-	-
Jaderberg et al. [78]	97.1	92.7	-	95.4	80.7	98.7	98.6	93.3	93.1	90.8	-	-	-	-	-	-	-
Jaderberg et al. [79]	95.5	89.6	-	93.2	71.7	97.8	97.0	93.4	89.6	81.8	-	-	-	-	-	-	-
Shi, Bai, and Yao [161] : CRNN	97.8	95.0	81.2	97.5	82.7	98.7	98.0	95.7	91.9	89.6	-	-	-	-	-	-	-
Shi et al. [162] : RARE	96.2	93.8	81.9	95.5	81.9	98.3	96.2	94.8	90.1	88.6	91.2	77.4	71.8	59.2	-	-	-
Lee and Osindero [91] : R2AM	96.8	94.4	78.4	96.3	80.7	97.9	97.0	-	88.7	90.0	-	-	-	-	-	-	-
Liu et al. [108] : STAR-Net	97.7	94.5	83.3	95.5	83.6	96.9	95.3	-	89.9	89.1	94.3	83.6	73.5	-	-	-	-
*Liu et al. [111]	94.1	84.7	-	92.5	-	96.8	92.2	-	-	-	-	-	-	-	-	-	-
*Mishra et al. [134]	78.1	-	46.7	78.2	-	88.0	-	-	67.7	60.2	-	-	-	-	-	-	-
*Su and Lu [174]	-	-	-	91.0	-	95.0	89.0	-	-	76.0	-	-	-	-	-	-	-
*Yang et al. [217]	97.8	96.1	-	95.2	-	97.7	-	-	-	-	93.0	80.2	75.8	69.3	-	-	-
Yin et al. [227]	98.7	96.1	78.2	95.1	72.5	97.6	96.5	-	81.1	81.4	-	-	-	-	-	-	-
*Cheng et al. [24] : FAN	99.3	97.5	87.4	97.1	85.9	†99.2	97.3	-	94.2	93.3	-	-	-	-	-	†85.3	-
Cheng et al. [25] : AON	99.6	98.1	87.0	96.0	82.8	98.5	97.1	-	91.5	-	94.0	83.7	73.0	76.8	68.2	-	-
Liu et al. [107] : Char-Net	-	-	83.6	-	84.4	-	93.3	-	91.5	90.8	-	-	73.5	-	60.0	-	-
*Liu et al. [121] : SqueezedText	97.0	94.1	87.0	95.2	-	98.8	97.9	93.8	93.1	92.9	-	-	-	-	-	-	-
*Zhan et al. [234]	98.1	95.3	79.3	96.7	81.5	-	-	-	-	87.1	-	-	-	-	-	-	-
*Bai et al. [8] : EP	99.5	97.9	88.3	96.6	87.5	98.7	97.9	-	94.6	94.4	-	-	-	-	73.9	-	-
Fang et al. [44]	98.5	96.8	86.7	97.8	86.7	99.3	98.4	-	94.8	93.5	-	-	-	-	71.2	-	-
Liu et al. [106] : EnEaCTC	-	-	82.0	-	80.6	-	-	-	92.0	90.6	-	-	-	-	-	-	-
Liu et al. [120]	97.3	96.1	89.4	96.8	87.1	98.1	97.5	-	94.7	94.0	-	-	73.9	62.5	-	-	-
Wang et al. [187] : MAAN	98.3	96.4	84.1	96.4	83.5	97.4	96.4	-	92.2	91.1	-	-	-	-	-	-	-
Sheng et al. [159] : NRTR	99.2	98.8	86.5	98.0	88.3	98.9	97.9	-	95.4	94.7	-	-	-	-	-	-	-
Gao et al. [47]	99.1	97.2	83.6	97.7	83.9	98.6	96.6	-	91.4	89.5	-	-	-	-	-	-	-
Shi et al. [163] : ASTER	99.6	98.8	93.4	97.4	89.5	98.8	98.0	-	94.5	91.8	-	-	78.5	79.5	76.1	-	-
Luo et al. [127] : MORAN	97.9	96.2	91.2	96.6	88.3	98.7	97.8	-	95.0	92.4	94.3	86.7	76.1	77.4	68.8	-	-
Luo et al. : MORAN-v2	-	-	93.4	-	88.3	-	-	-	94.2	93.2	-	-	79.7	81.9	73.9	-	-
Chen et al. [20]	99.5	98.7	94.6	97.4	90.4	98.8	98.3	-	95.3	93.5	94.7	89.6	82.8	81.3	77.4	-	-
Xie et al. [205] : CAN	97.0	94.2	80.5	96.9	83.4	98.4	97.8	-	91.0	90.5	-	-	-	-	-	-	-
*Liao et al. [101] : CA-FCN	†99.8	98.9	92.0	98.8	82.1	-	-	-	-	91.4	-	-	-	-	78.1	-	-
*Li et al. [94] : SAR	99.4	98.2	95.0	98.5	91.2	-	-	-	-	†95.8	91.2	86.4	89.6	89.6	78.8	-	-
Zhan et al. [233] : ESIR	99.6	98.8	93.3	97.4	90.2	-	-	-	91.3	-	-	79.6	83.3	76.9	-	-	-
Zhang et al. [238] : SSDAN	-	-	83.8	-	84.5	-	-	-	92.1	91.8	-	-	-	-	-	-	-
*Yang et al. [216] : SCRN	99.5	98.8	94.4	97.2	88.9	99.0	98.3	-	95.0	93.9	-	-	80.8	87.5	78.7	-	-
*Yang et al. [192]	-	-	94.2	-	89.0	-	-	-	92.0	95.7	90.1	81.7	83.7	74.8	-	-	-
Wang et al. [195] : GCAM	-	-	93.9	-	91.3	-	-	-	95.3	95.7	-	-	85.7	83.3	83.5	-	-
Jeonhuh et al. [4]	-	-	87.9	-	87.5	-	-	-	94.4	92.3	-	-	79.2	74.0	71.8	-	-
Huang et al. [76] : EPAN	98.9	97.8	94.0	96.6	88.9	98.7	98.0	-	95.0	94.5	91.2	86.4	79.4	82.6	73.9	-	-
Gao et al. [48]	99.1	97.9	81.8	97.4	82.7	98.7	96.7	-	89.2	88.0	-	-	-	-	62.3	-	-
*Qi et al. [147] : CCL	99.6	99.1	91.1	98.0	85.9	99.2	†98.8	-	93.5	92.8	-	-	-	-	72.9	-	-
*Wang et al. [193] : ReLEFA	99.2	98.1	90.9	97.7	-	-	-	-	-	82.7	-	-	-	-	82.3	68.5	-
*Zhu et al. [242] : HATN	-	-	88.6	-	82.2	-	-	-	91.3	91.1	-	-	73.5	75.7	70.1	-	-
*Zhan et al. [235] : SF-GAN	-	-	63.0	-	69.3	-	-	-	-	61.8	-	-	48.6	40.6	39.0	-	-
Liao et al. [98] : SAM	99.4	98.6	93.9	98.6	90.6	98.8	98.0	-	95.2	95.3	-	-	82.2	87.8	77.3	-	-
*Liao et al. [98] : seq-SAM	†99.8	†99.3	95.3	†99.1	91.8	99.0	97.9	-	95.0	95.3	-	-	83.6	88.5	78.2	-	-
Wang et al. [197] : DAN	-	-	94.3	-	89.2	-	-	-	95.0	93.9	-	-	80.0	84.4	74.5	-	-
Wang et al. [198]	-	-	92.5	98.0	87.2	-	-	-	93.2	91.3	-	-	77.4	78.9	75.6	-	-
*Wan et al. [185] : TextScanner	99.7	99.1	93.9	98.5	90.1	-	-	-	92.9	-	-	84.3	83.3	79.4	-	-	-
*Hu et al. [73] : GTC	-	-	†95.8	-	†92.9	-	-	-	95.5	94.4	-	-	85.7	†92.2	79.5	-	-
Luo et al. [128]	99.6	98.7	95.4	98.9	92.7	99.1	98.8	-	96.3	94.8	95.5	92.2	85.4	89.6	83.7	-	-
*Litman et al. [103]	-	-	93.7	-	92.7	-	-	-	†96.3	93.9	-	-	†86.9	87.5	82.2	-	-
Yu et al. [229]	-	-	94.8	-	91.5	-	-	-	95.5	-	-	85.1	87.8	82.7	-	-	-
Qiao et al. [149]	-	-	93.8	-	89.6	-	-	-	92.8	-	-	81.4	83.6	80.0	-	-	-

- The first protocol evaluates the algorithm performance in several aspects, including *precision*, *recall*, and *F-score* based on *NED*. According to the matching relationship between the predicted and ground truth bounding boxes, the 1-*NED* of the predicted text and ground truth text serves as *precision* and *recall* score. The *F-score* is the harmonic average of the score of *precision* and *recall*. This is a mainstream metric to evaluate detection and recognition performance simultaneously. The protocol is widely used in [67], [176], [27], [114], [138].
- The second protocol measures the algorithm performance by the average *NED*, namely, *AED*. In particular, the *NED* between the predicted text and the corresponding ground truth are calculated. Then, all the *NEDs* are summed and divided by the number of test images,

Table 5. Performance comparison of end-to-end system algorithms on benchmark datasets. ‘50’ and ‘Full’ are lexicon sizes. ‘None’ means lexicon-free. ‘S’, ‘W’, and ‘G’ stand for three different vocabularies, i.e., strongly contextualised, weakly contextualised, and generic. ‘*’ represents testing with multiple scales. The **bold** represents the best results.

Method	SVT		IC03		IC11		IC13						IC15						Total-text	
							End-to-end			Spotting			End-to-end			Spotting			Full	None
	50	None	50	Full	None		S	W	G	S	W	G	S	W	G	S	W	G		
Wang et al. [190]	38.0	-	68.0	51.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Wang et al. [196]	46.0	-	72.0	67.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Jaderberg et al. [81]	56.0	-	80.0	75.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Alsharif et al. [2]	48.0	-	77.0	70.0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Yao et al. [218]	-	-	-	-	-	48.6	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Neumann et al. [143]	68.1	-	-	-	-	-	-	-	45.2	-	-	-	35.0	19.9	15.6	35.0	19.9	15.6	-	-
Jaderberg et al. [78]	76.0	53.0	90.0	86.0	78.0	76.0	-	-	-	-	-	76.0	-	-	-	-	-	-	-	-
*Liao et al. [100] : TextBoxes	84.0	64.0	-	-	-	87.0	91.0	89.0	84.0	94.0	92.0	87.0	-	-	-	-	-	-	-	-
Büsta et al. [15] : Deep TextSpotter	-	-	-	-	-	-	89.0	86.0	77.0	92.0	89.0	81.0	54.0	51.0	47.0	58.0	53.0	51.0	-	-
Li et al. [93]	84.9	66.2	-	-	-	87.7	91.1	89.8	84.6	94.2	92.4	88.2	-	-	-	-	-	-	-	-
Lyu et al. [129] : Mask TextSpotter	-	-	-	-	-	-	92.2	91.1	86.5	92.5	92.0	88.2	79.3	73.0	62.4	79.3	74.5	64.2	71.8	52.9
He et al. [70]	-	-	-	-	-	-	91.0	89.0	86.0	93.0	92.0	87.0	82.0	77.0	63.0	85.0	80.0	65.0	-	-
*Liu et al. [112] : FOTS	-	-	-	-	-	-	92.0	90.1	84.8	95.9	93.9	87.8	83.6	79.1	65.3	87.0	82.4	68.0	-	-
*Liao et al. [99] : TextBoxes++	84.0	64.0	-	-	-	-	93.0	92.0	85.0	96.0	95.0	87.0	73.3	65.9	51.9	76.5	69.0	54.4	-	-
Liao et al. [98] : Mask TextSpotter	-	-	-	-	-	-	93.3	91.3	88.2	92.7	91.7	87.7	83.0	77.7	73.5	82.4	78.1	73.6	77.4	65.3
*Xing et al. [210] : CharNet	-	-	-	-	-	-	-	-	-	-	-	-	85.1	81.3	71.1	-	-	-	-	69.2
Feng et al. [45] : TextDragon	-	-	-	-	-	-	-	-	-	-	-	-	82.5	78.3	65.2	86.2	81.6	68.0	74.8	48.8
Qin et al. [150]	-	-	-	-	-	-	-	-	-	-	-	-	85.5	81.9	69.9	-	-	-	-	70.7
Wang et al. [188] : Boundary	-	-	-	-	-	-	88.2	87.7	84.1	-	-	-	79.7	75.2	64.1	-	-	-	76.1	65.0
Qiao et al. [148] : Text Perceptron	-	-	-	-	-	-	91.4	90.7	85.8	94.9	94.0	88.5	80.5	76.6	65.1	84.1	79.4	67.9	78.3	69.7

Table 6. Performance comparison for competitions. NED stands for the normalized edit distance.

Competition	Detection			End-to-End		
	Team Name	Protocol	Result (%)	Team Name	Protocol	Result (%)
RCTW	Foo & Bar	F-score	66.10	NLPR_PAL	1 - NED	67.99
MTWI	nelslip(iflytek&ustc)	F-score	79.60	nelslip(iflytek&ustc)	F-score	81.50
LSVT	Tencent-DPPR Team	F-score	86.42	Tencent-DPPR Team	F-score	60.97
ArT	pil_maskrcnn	F-score	82.65	baseline_0.5_class_5435	F-score	50.17
ReCTS	SANHL	F-score	93.36	Tencent-DPPR	1 - NED	81.50
MLT	Tencent-DPPR Team	F-score	83.61	Tencent-DPPR Team & USTB-PRIR	F-score	59.15

and the result is called *AED*. Specifically, a lower *AED* means a better performance. This protocol evaluation was introduced in [164] to improve the fairness for long text detection and recognition, which is practical useful for real-world systems.

These two types of evaluation protocols evaluate the algorithm from different perspectives. As illustrated in Table 6, the performances of winning systems of several recent end-to-end competitions indicate that the problem of end-to-end recognition remains unsolved.

4.3 Discussion

Various new challenging datasets inspire new research that promotes the progress in the field. However, it is hard to assess whether and how a newly proposed algorithm improves upon the current art because of the varieties of different datasets, priors, evaluation protocols, and testing environments. Therefore, a holistic and fair comparison is necessary for future work [4], [118].

Recent datasets and competitions show that the community is moving toward more challenging text recognition tasks (e.g., from horizontal text to irregular text, and from Latin text to multilingual text). Beyond the challenges, high-quality annotations are also critical for a good dataset. Moreover, new datasets and competitions may bridge the gap between academia and industry.

5 DISCUSSION AND FUTURE DIRECTIONS

Text has played an important role in human lives. Automatically reading text in natural scenes has a great practical value. Therefore, scene text recognition has become an important and vibrant research area in computer vision and pattern recognition. This paper summarizes the fundamental

problems and the state-of-the-art methods associated with scene text recognition, introduces new insights and ideas, and provides a comprehensive review of publicly available resources. In the past decades, there have been substantial advancements in innovation, practicality, and efficiency of recognition methods. However, there is ample room remaining for future research:

- **Generalization Ability.** Generalization ability refers to the ability of recognition algorithms to be effective across a range of inputs and applications. Although the recognition algorithms trained by the synthetic datasets achieve good performance on several realistic evaluation datasets, they fail to adapt to varying inputs, such as text instances with longer characters, smaller sizes, and unseen font styles. Moreover, most recognition algorithms are sensitive to environmental interferences and hard to deal with real-world complexity, e.g., the poor performance reported on the COCO-Text dataset. Therefore, researchers and practitioners have to train models from scratch based on specific inputs and scenarios.

In contrast, humans are adept at recognizing different styles of text under complex scenarios with little supervision learning, which indicates that there still exists a giant gap between the current understanding level of machines and human-level performance. In addition to simply employing rich and diverse data as training samples, a feasible solution might be to explore the unique and essential representation of text, such as visual-level and semantic-level.

- **Evaluation Protocols.** Numerous approaches proposed in recent years claimed to have pushed the boundary of the technology. However, the inconsistency of datasets, priors, and testing environments makes it difficult to fairly evaluate the reported numbers at face value in Table 4 and Table 5. Researchers and practitioners have to confirm and compare the experimental settings in newly proposed algorithms. For example, which training datasets were used, e.g., synthetic datasets, realistic datasets or a mixture of both? which annotations were used, e.g., word-level, character-level or pixel-level? Considering this, a fair comparison is required in the community. For example, future work might report recognition performance on the unified training/testing datasets or even report recognition performance on a single model, i.e., evaluate the performance of the same model across different datasets. Moreover, clear and detailed experimental settings introduced in papers are also important in advancing research progress.

- **Data Issues.** Most deep learning algorithms highly depend on a sufficient amount of high quality data. The existing realistic datasets only contains thousands of data samples, which is relatively small for training a accurate scene text recognizer. Moreover, manually collecting and annotating large amount of real-world data will involve huge efforts and resources. Therefore, there are two aspects to be considered. On one hand, synthesizing as realistic and effective data as possible has a potential in the community. Compared with realistic datasets, multi-level annotation information (i.e., word-level, character-level and pixel-level) can be easily obtained during synthesizing, which can be used to train data-hungry algorithms. For example, some researchers [123] are working to synthesis realistic text instances by a 3D engine. On the other hand, approaches of using unlabeled real-world data are worth considering in the future.

It is valuable to explore how to use the existing data efficiently. For example, with the emergence of many realistic datasets, we should reconsider whether unified synthetic datasets are the only choice for training models and then evaluated with realistic datasets. (Such strategy is widely adopted in most of current researches.) The balance between realistic datasets and synthetic datasets needs to be further developed. Moreover, developing efficient data augmentation approaches for text might be a feasible and promising solution, which should focus more on the style of multi-objects.

- **Scenarios.** The research aims to improve human quality of life. However, for STR, the gap between the research and applications still exists. In practical applications, text usually appears with worse image quality, more complex backgrounds, and more noise, which requires the recognition systems with the ability to deal with real-world complexity. Meanwhile, for simple but private vision-based scenarios, such as bank cards, recognition performance is especially important. Thus, researchers and practitioners should not be limited to several standard benchmarks. Challenges in real-world applications may provide new research opportunities and advance research progress in the future, such as multilingual text recognition in modern cities, ultra-high precision recognition in private scenarios, and fast text recognition for mobiles.
- **Image Preprocessing.** To improve the recognition performance of algorithms, increasingly complex recognizers have become a new trend in the community. However, this is not the only perspective worth considering. Some potential image preprocessing issues deserve the attention of researchers, such as TextSR [146] and background removal [128], which can significantly reduce the difficulties of STR and improve performance from a new perspective.
- **End-to-End Systems.** Constructing a real-time and efficient end-to-end system has attracted the interest of researchers and practitioners. However, the performance of end-to-end systems remains far behind compared with that of OCR in scanned documents. Some difficulties should be considered, such as efficiently bridging and sharing information between text detection and recognition, balancing the significant differences in learning difficulty and convergence speed between text detection and recognition, and improving joint optimization. In this area, there is much work to be done. Furthermore, it is worth considering whether end-to-end solutions are necessary for industrial applications.
- **Languages.** Representatives of multiple cultures live and communicate in modern cities. Multilingual text recognition is critical to human communication as well as smart city development. In addition to construct large-scale synthetic/realistic multilingual training datasets, a feasible solution might be combined with script identification. Moreover, although many recognition algorithms exist, most of them focus on Latin text only. Recognition of non-Latin has not been extensively investigated, such as Chinese scene text, which is large-scale category text and has unique characteristics compared with Latin text. Existing recognition algorithms cannot be well generalized to different languages. Developing language-dependent recognition algorithms for specific language might be a feasible solution.
- **Security.** As STR algorithms can be adapted to many private vision-based scenarios (such as bank cards, ID cards, and driver licenses), the security of recognition approaches is very important. Despite high performance, most deep learning-based text recognizers are highly vulnerable to adversarial examples. Strengthening the security of STR algorithms will be a potential direction in the future.
- **STR + NLP.** NLP is a bridge in human-computer communication. Meanwhile, text is the most important carrier of communication and perception in the world. A combination of NLP and STR may be an important trend in various fields, such as text VQA [171], [199], document understanding [84], and information extraction [110], [35].

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