Text Detection & Recognition in the Wild for Robot Localization

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Abstract—Signage is everywhere and a robot should be able to take advantage of signs to help it localize (including Visual Place Recognition (VPR)) and map. Robust text detection & recognition in the wild is challenging due such factors as pose, irregular text, illumination and occlusion. We propose an end-to-end scene text spotting model that simultaneously outputs the text string and bounding boxes. This model is more suitable for VPR. Our central contribution is introducing utilizing an end-to-end scene text spotting framework to adequately capture the irregular and occluded text regions in different challenging places. To evaluate our proposed architecture’s performance for VPR, we conducted several experiments on the challenging Self-Collected Text Place (SCTP) benchmark dataset. The initial experimental results show that the proposed method outperforms the SOTA methods in terms of precision and recall when tested on this benchmark.

I. INTRODUCTION

We live in a visual world, signage is everywhere. Whether it is a street sign, a billboard, a house or room number or labels such as a license plate or a person’s name; signage provides us useful information in terms of location and identity. There have been many classifiers developed that are able to identify street signs or license plates with highly constrained priors on the method that do not allow their extension to general text in the wild detection and recognition. However, to take advantage of all the signage available, we need to be able to detect signage (i.e., text) anywhere (i.e., in the wild). OCR is a well solved problem for text detection and recognition in highly constrained environments however detecting and recognizing text anywhere is a challenging problem.

Signage can help a robot localize or map an environment. Typically for SLAM processes, direct (i.e., pixel) or indirect features are used. Signage can provide a coarse localization globally when the signage indicates an address or location. Also the letters and numbers in a sign and their perspective can be used to determine relative pose if we assume the signage is on a planar surface or even just vertical wrt the ground plane. Visual Place Recognition (VPR)\(^{[15, 22, 41, 44, 69]}\) aims to aid a vision guided system to localize wrt a previously visited place. VPR has uses in loop closure detection for visual SLAM and localization in general. Challenges in VPR include appearance variation due to perceptual aliasing, illumination, viewpoint changes, pose, weather, seasons to name a few. Most techniques are focused on features (i.e., indirect)\(^{[29]}\) and sets of these features (e.g., BOW Bag of Words) methods.

Text spotting in the wild images is also called end-to-end scene text detection and recognition\(^{[40, 52]}\). Simultaneous text detection and recognition go hand in hand. In scene text detection, the goal is to localize words in the image, and for scene text recognition, the aim is to convert the patch of cropped word images into a sequence of characters. Like scene text detection and recognition tasks, scene text spotting also encounters different challenging problems, including irregular text, illumination variations, low-resolution text, occlusion, etc\(^{[50]}\).

Previous methods in scene text detection and recognition have utilized convolutional neural network (CNN) as a feature extractor\(^{[19, 37, 56, 57]}\) and Recurrent Neural Networks (RNN)\(^{[4, 21, 59]}\) for capturing sequential dependency. Despite achieving promising performances on various challenging benchmark datasets\(^{[9, 16, 23–26, 35, 42, 46, 48, 58, 60, 65–67]}\), it has been shown that there are two main challenges for detecting or recognizing text in the wild images that has been studied in the past years. (1) Irregular text refers to the text with arbitrary shapes that usually have severe orientation and curvature, and (2) occlusion, which makes poor performance on the existing methods\(^{[4, 5, 36, 61]}\) due to their reliance on the visibility of the target characters in the given images. Furthermore, CNN’s have two significant drawbacks: (1) they have problems in capturing long-range dependencies (e.g., arbitrary relations between pixels in spatial domains) due to their fixed-size window operation\(^{[70]}\), (2) they suffer from dynamical adoption to the changes to the inputs because the convolution filter weights are tuned to a specific training distribution\(^{[27]}\).

Recent end-to-end scene text spotting methods\(^{[28, 54, 55, 68]}\) utilized transformers\(^{[64]}\) in their architecture and achieved superior performance in many benchmarks\(^{[9, 67]}\). Transformers\(^{[64]}\), and their variations\(^{[7, 10, 70]}\), are a new deep learning architecture that mitigates the issues mentioned above for CNNs; Unlike Recurrent Neural Networks (RNNs), transformers are models that learn how to encode and decode data by looking not only backward but also forward to extract relevant information from a whole sequence allowing conducting complex tasks such as machine translation\(^{[64]}\), speech recognition\(^{[8]}\), and recently in computer vision\(^{[7, 12, 27]}\). The attention mechanism allows the transformers to reason more effectively and focus on the relevant parts of the input data (e.g., a word in a sentence for machine translation and a character of a word in a text image for detection and recognition) as needed.

Visual place recognition (VPR)\(^{[22]}\) aims to recognize the previously visited places using visual information with resilience to perceptual aliasing, illumination, and viewpoint
changes. Text that appears in the wild images, such as street signs, billboards, and shop signage, usually carries extensive discriminative information. VPR task can take advantage of these scene texts with high-level information for previously visited place recognition.

This paper leverages a pre-trained end-to-end transformer-based text spotting framework for the VPR task. Unlike [22] that used two separate modules of detection and recognition for extracting the text regions, our model can directly read the text instances from the given frame in an end-to-end manner. Furthermore, by equipping a masked autoencoder (MAE) [18] as a backbone, our proposed model is more robust in capturing occluded text instance regions, which makes it more suitable for visual place recognition. Our main contributions are as follows: (1) We utilize an end-to-end transformer-based scene text spotting pipeline for the VPR application for the first time. Our model can handle arbitrary shapes text with polygon bounding boxes and output word instances simultaneously. (2) We provide a quantitative and qualitative comparison of our method with state-of-the-art (SOTA) techniques.

II. RELATED WORK

A. End-to-end Scene Text Detection and Recognition

Scene text spotting aims to detect and recognize text instances from a given image end-to-end [14,31,33,38,39,43,47,57]. Similar to different computer vision tasks, deep learning techniques using CNN/RNN-based methods and transformer-based methods are dominant frameworks in scene text spotting.

Early methods [31] in scene text spotting have mainly utilized a deep-learning convolutional neural network (CNN) as a feature extractor [20] and Recurrent Neural Networks (RNN) [4,21,59] to read horizontal scene text. For example, Li et al. [31] combined the detection and recognition framework to present the first text spotting method by using a shared CNN backbone encoder, following by RoIPooling [57] as detection. Then the resulted features are fed into RNN recognition to output the final word instances for a given input image. FOTS [38] utilized an anchor-free CNN-based object detection framework that improved both the training and inference time. It also used a RoIReact module for reading rotated text instances.

Since text in the wild images appear in arbitrary shapes including multi-oriented and curved, several methods [14,33,39,43,47] targeted reading these type of text instances. These methods usually used a CNN-based segmentation network with multiple post-processing stages to output polygon box coordinates for the final irregular texts. For instance, in [47], a RoIMask is used to connect both the detection and recognition module for capturing arbitrary shaped text. Liu [39] leveraged a Bezier curve representation for the detection part, followed by a Bezier Align module to rectify the curved text instances into a regular text before feeding it to the attention-based recognition part. Some methods [6,55] targeted spotting individual characters and merging them to output the final arbitrary shape text instance.

Recently with the advancement of transformers [64] in computer vision fields [17,27,63], several SOTA scene text spotting methods [3,13,30,49,51,53] proposed to take the benefit of transformer-based pipelines in their framework. These methods achieved superior performance in both regular and irregular benchmark datasets. For example, Kittenplon et al. [28] utilized a transformer-based detector, Deformable-DETR’s [70], as its primary framework by proposing a multi-task prediction head that can output word instances and box coordinates of an arbitrary shape text. [68] used transformers as the main block for an end-to-end text spotting framework for text detection and recognition in wild images. These methods removed the dependency of region-of-interest operations and post-processing stages in their framework. Thus, they can output both Bezier curve and polygon representations and achieve superior benchmark performance. Very recently, Raisi et al. [54] proposed an end-to-end framework for scene text spotting that is also capable of improving the recognition performance for an adverse situation like occlusion. This method utilized an MAE in their pipeline equipped with a powerful detector, namely deformable-DETR [70], to capture the arbitrary shape of occluded text instance in the wild images. In this work, we use a pre-trained model of [54] for the VPR task.

III. METHODOLOGY

For a complete text reading, simultaneous text detection and recognition are required. Unlike step-wise detection and recognition, the end-to-end framework will improve the overall speed by eliminating multiple processing steps. Furthermore, an end-to-end transformer is expected to offer higher accuracy compared to previous end-to-end CNN-based approaches [38,39].

A. Scene Text Spotting Architecture

The overall framework of our proposed method is shown in Figure 1.

**Backbone:** Inspired [32], the proposed model uses a pre-trained models of the Vision Transformer architecture (ViT) [12] as the backbone. The input image is first split into a non-overlapping sequence of patches. After masking a large set of the input patches (∼75%) and adding the 1D position embedding, these patches are passed into transformer blocks containing several multi-head self-attention and feed-forward modules. However, the final output of the transformer encoder backbone is single-scale due to the columnar structure of ViT, which makes them inadequate for detecting multi-scale text instances. To address this, we utilize a multi-scale adapter module [32]. It is worth mentioning that we use a pre-trained MAE [18] (ViT-Base/16) as the backbone for feature extraction. This backbone was further fine-tuned on 36 classes of alphanumeric characters.

**Multi-scale adapter:** Inspired from [32,54], we adapt the single-scale ViT into the multi-scale FPN for capturing different resolution of text regions. The multi-scale feature map module utilizes the idea of up-sampling or down-sampling into the intermediate single-scale ViT’s feature map.
Fig. 1: Block diagram of the proposed scene text spotting architecture using transformer for VPR [54]. Unlike the step-wise pipeline in [22], our model output the bounding box coordinates and the word instances in an end-to-end manner for the VPR task (See section III for more details). Best viewed when zoomed.

with columnar structure [32]. The resulted multi-scale feature maps are then fed into a modified detector [70] for detecting and recognizing word instances.

**Text predictor:** After feature extraction and multi-scaling, the resulted feature maps are fed to the text of the final module to detect and recognize the text instance of a given image. As shown in Figure 1, the proposed text predictor leverages a modified Deformable-DETR [70] with multi-task prediction head. During training, the encoder’s multi-head self-attention detector learns how to separate individual character and word instances in the scene image by performing global computations. The decoder typically learns how to attend to a different part of characters in words by using different learn-able vectors (so-called object queries). After training, the multi-task head (last layer of the decoder) can directly predict both absolute bounding box coordinates and sequence of characters, eliminating the use of any hand-designed components and post-processing like anchor design and non-max suppression. After reading the text instances from the scene images, we implement the same text filtering criteria as introduced in [22] for comparing the query and inference frames.

**IV. EXPERIMENTAL RESULT**

**A. Datasets and Evaluation Metric**

The Self-Collected TextPlace (SCTP) Dataset [22] is designed explicitly for visual place recognition tasks in urban places. The images of this dataset are captured using a side-looking mobile phone camera. These images include three pairs of map and query sequences in outdoor streets and an indoor shopping mall and contain significant challenging scenarios, including high dynamics, random occlusions, severe illumination changes, irregular text instances, and viewpoint changes. To compare the performance of our proposed model with SOTA methods [1, 2, 22], we use the precision recall evaluation measurement described in [22, 62].

**B. Quantitative Comparison**

The quantitative results of our proposed model with several SOTA methods [1, 2, 11, 22, 45] on SCTP datasets [22] are shown in Table I. Our model achieved the best performance in terms of recall for this dataset, which contains significant challenging like irregular and partially occluded text instances. This performance confirms the effectiveness of our proposed method for VPR.

**C. Qualitative Results**

Figure 2 illustrates qualitative results for the [22] dataset. Our model successfully read challenging text instances of both query and reference frames. We also compare our model with some of SOTA techniques [2, 22, 45] in Figure 3; As shown, our proposed text spotting model matches correctly the query frame with frame in inference.

We also experiment with measuring the inference speed of our model and comparing it with [22] in terms of Frames Per Second (FPS). To that effect and for a fair comparison, we use an RTX 3080Ti GPU that has a similar memory used in [22] and presented in [34]; Our model outperformed the TextPlace method by a large margin achieving ~11 FPS in compare to 2.3 FPS in [22].
frames are correct matches, while the ones with red frames are incorrect matches. ToDayGAN is not compared for the sequences in day-day sequence.

Fig. 2: Query image and matching reference examples of [22] dataset. Our proposed model detects and recognizes the most challenging text instances required to match the query (top column) and reference (bottom column) frames. Best viewed in color when zoomed.

| Query | Street 1 | Street 1 | Street 2 |
|-------|---------|---------|---------|
| SeqSLAM | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) |
| NetVLAD | ![Image](image4.png) | ![Image](image5.png) | ![Image](image6.png) |
| TextPlace | ![Image](image7.png) | ![Image](image8.png) | ![Image](image9.png) |
| Ours | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |

Fig. 3: Qualitative comparison of the proposed model with SOTA methods [2, 22, 45] on the SCTP dataset. The correct and incorrect results are bounded with green and red colors.

It is worth mentioning that our proposed model performs poorly on extremely low-resolution and blurry text instances. However, these challenges are still open in many SOTA text detection and recognition in the wild methods.

### V. CONCLUSIONS

We presented an end-to-end scene text spotting model for the visual place recognition task. The proposed model has leveraged a robust and SOTA backbone of pre-trained MAE and a modified multi-task transformer detector. Our experimental results have shown that the proposed model outperforms SOTA models in VPR, which confirms the robustness of our end-to-end scene text detection and recognition model. Other applications besides VPR include different facets of localization and mapping. Being able to detect and recognize text allows the potential to leverage semantics and the features related to the detected text to better localize and map as opposed to just using indirect features [29].

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### VI. APPENDIX

The TextPlace [22] model uses the pre-trained model of Textboxes++ [34] algorithm as the main text extraction in their framework for the VPR application. In this section, we conduct additional experiments to compare our proposed model with Textboxes++ [34]; To that effect, we provide quantitative and qualitative results to show how our model performs for text instances that appear in the wild images using the benchmark dataset, ICDAR15 [25], as in [34]. The ICDAR15 is a challenging dataset that contains various indoor and outdoor multi-oriented text instances. Like most of the images in the VPR applications, this dataset has a wide variety of blurry and low-resolution text. The text instances in this dataset are annotated in quadrilateral bounding box annotations.

#### Quantitative Comparison
Table II shows the quantitative comparison of our model and Textboxes++ using the well-known text detection and end-to-end text spotting evaluation metrics [25]. As seen, our proposed approach outperformed the [34] in both detection and end-to-end spotting tasks. It achieves an H-mean detection performance of 86.5% compared to 82.9% in [34]. It also surpasses the Textboxes++ method with a large margin of ∼16% in end-to-end F-measure performance. Furthermore, as described in §IV, our model is more suitable for real-time detection and recognition as it provides a better FPS. These performances confirm our models’ well generalization and efficiency on challenging and unseen VPR dataset, SCTP (see Table I).

#### Qualitative Comparison
To see how our proposed algorithm performs in challenging cases of the ICDAR15 dataset, we also provide a qualitative comparison of our model with failure cases in [34]. As shown in Figure 4, Our method successfully predicted most of the failure cases. Since text instances in the wild images usually appear with arbitrary shapes, this is important to use a model that better captures any shape of the scene text. The results in the last column in Figure 4 also show that our proposed pipeline is capable of accurately outputting polygon bounding boxes for curved text instances, whereas Textboxes++ fails to detect.

| Model | Detection | E2E | FPS |
|-------|-----------|-----|-----|
| TextBoxes++ [34] | 87.8 | 78.5 | 82.9 | 51.9 | 2.3 |
| Ours | 90.2 | 83.1 | 86.5 | 68.2 | 11.0 |

*Note: E2E denotes end-to-end text spotting, and FPS is Frames per second. Best performance is highlighted in bold.*
Fig. 4: Comparison between our proposed end-to-end model (bottom row) with Textboxes++ [34] algorithm (top row). The red boxes in the top row images show the failure cases (Images are taken from [34]), and the cyan text and boxes show our results. The orange arrows point to text regions where our model could successfully predict failure text instances of Textboxes++. 