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Text Detection in Natural Scene Images using CRAFT and EAST

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Abstract

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1 Introduction

Text is arguably one of the most essential form of communication. According to Long et al. (2020):

“As the written form of human languages, text makes it feasible to reliably and effectively spread or acquire information across time and space. In this sense, text constitutes the cornerstone of human civilization.” (Long et al. 2020)

In the modern world, text as a medium of communication is not only consumed by humans but has claimed its place in the world of technology. However, text detection in natural scene images is proven to be challenging. Compared to detecting text on handwritten materials, the randomness of a natural scene is a big hurdle to overcome. This paper aims to test and evaluate the two proposed methods on their performance in detecting natural-scene texts. It begins by observing the interference found on natural scenes followed by introducing and giving an overview of CRAFT and EAST. It then provides an explanation of the evaluation dataset. Subsequently, the performance review of the algorithm will be presented, which is obtained by testing the preferred method on the aforementioned dataset.

2 Challenges of Natural Text Detection

Natural scene images could be classified as images which are taken in uncontrolled environments, with any device ranging from smartphones to professional cameras. These images are snapshots of things in the real world.



(a) A scenery



(b) A billboard

Figure 1: Samples of natural scene images.

The random nature of the real world, combined with the diversity of available devices introduced some factors which make natural text detection a greater

challenge than detecting structured text in documents. Mancas-Thillou & Goselin (2007) mentioned some conditions that are found in natural scene which may significantly impact text detection procedure. They are:

- Raw sensor image and sensor noise
- Viewing angle
- Blur
- Lighting
- Resolution
- Non-paper objects
- Non-planar objects

Although devices have evolved to a point where most of handheld devices are capable of shooting in a high resolution, low-end handheld cameras and older models still struggle in this sector. Uncontrolled environment, combined with the possible lack of stabilization from the equipment can cause blur (Rosebrock 2018). Also, there are countless factors such as the time of the day, weather, camera flash, and many others which may impact the lighting conditions, further hindering the ability to detect text. Non-paper objects such as glass and plastic may reflect images, and non-planar objects such as text wrapped around a bottle becomes distorted and deformed (Rosebrock 2018). Additionally, there might be patterns that are extremely similar to text, or occlusions caused by foreign objects, which may potentially lead to confusion and mistakes (Long et al. 2020).

3 Methodology

3.1 Overview of EAST

According to Zhou et al. (2017), the key component of EAST is a neural network model, which is trained to directly predict the existence of text instances and their geometries from full images (Zhou et al. 2017). Hence, the abbreviation EAST: Efficient and Accurate Scene Text Detector.

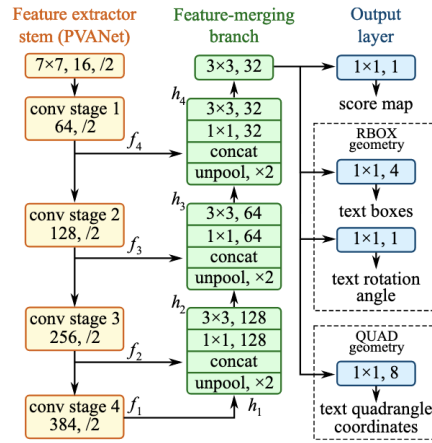


Figure 2: Schematic view of EAST, adopted from Figure 3 of Zhou et al. (2017)

As claimed by Zhou et al. (2017), EAST is among the most efficient text detectors that achieve state-of-the-art performance on benchmarks. The idea of the network is described shortly below:

“... we adopt the idea from U-shape (Ronneberger et al. 2015) to merge feature maps gradually, while keeping the upsampling branches small. Together we end up with a network that can both utilize different levels of features and keep a small computation cost.” (Zhou et al. 2017)

It is capable of predicting text on 720p images, running at an average of 13 FPS. The fastest setting, which reached a speed of 16.8 FPS was achieved on a combination of their algorithm with PVANET on 720p images using NVIDIA Titan X graphics card. (Zhou et al. 2017). The training of the network is further described as follow:

“The network is trained end-to-end using ADAM (Kingma & Ba 2014) optimizer. To speed up learning, we uniformly sample 512x512 crops from images to form a minibatch of size 24. Learning rate of ADAM starts from 1e-3, decays to one-tenth every 27300 minibatches, and stops at 1e-5. The network is trained until performance stops improving.” (Zhou et al. 2017)

3.2 Overview of CRAFT

CRAFT stands for Character Region Awareness for Text Detection. According to Baek et al. (2019), CRAFT is a novel text detector which localizes the individual character regions and links the detected characters to a text instance (Baek et al. 2019).

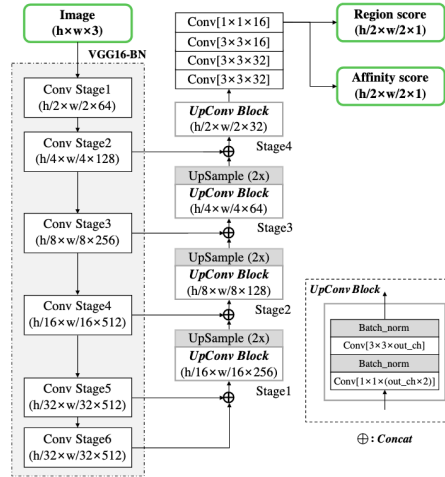


Figure 3: Structure of Craft, adopted from Baek et al. (2019)

As stated in the original paper, CRAFT adopts a fully convolutional network architecture based on VGG-16 (Simonyan & Zisserman 2015) with batch normalization as its backbone (Baek et al. 2019). It is further described as follow:

“Our model has skip connections in the decoding part, which is similar to U-Net (Ronneberger et al. 2015) in that it aggregates low level features. The final output has two channels as score maps: the region score and the affinity score. The network architecture is schematically illustrated in figure 3 (Baek et al. 2019).”

3.3 Testing

4 Results and Evaluation

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5 Conclusion

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References

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