A Binary Convolutional Encoder-decoder Network for Real-time Natural Scene Text Processing

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Abstract

In this paper, we develop a binary convolutional encoder-decoder network (B-CEDNet) for natural scene text processing (NSTP). It converts a text image to a class-distinguished salience map that reveals the categorical, spatial and morphological information of characters. The existing solutions are either memory consuming or run-time consuming that cannot be applied to real-time applications on resource-constrained devices such as advanced driver assistance systems. The developed network can process multiple regions containing characters by one-off forward operation, and is trained to have binary weights and binary feature maps, which lead to both remarkable inference run-time speedup and memory usage reduction. By training with over 200,000 synthesis scene text images (size of $32 \times 128$), it can achieve 90% and 91% pixel-wise accuracy on ICDAR-03 and ICDAR-13 datasets. It only consumes 4.50 ms inference run-time realized on GPU with a small network size of 2.14 MB, which is up to $8 \times$ faster and 96% smaller than its full-precision version.

1 Introduction

The success of convolutional neuron network (CNN) has resulted in a potential general machine learning engine for various computer vision applications [LeCun et al., 1998, Krizhevsky et al., 2012] as well as for the natural scene text processing (NSTP), such as text detection, recognition and interpretation from images. Applications, such as Advanced Driver Assistance System (ADAS) for road signs with text, however require a real-time processing capability that is beyond the existing approaches [Jaderberg et al., 2014a] from processing functionality, efficiency and latency.

A general NSTP system is based on a two-phase end-to-end pipeline that firstly segments the text region from the original image and then performs recognition of the cropped image. In recognition phase, the cropped image is transformed into text sequence that will be further processed by the Natural Language Processing (NLP) module [Chowdhury, 2003]. There are two categories of methods that can be applied, character-level method [Wang et al., 2012, Bissacco et al., 2013] and word-level method [Jaderberg et al., 2014a,b]. The character-level method performs an individual character detection and recognition. It relies on a multi-scale sliding window strategy combined with a convolutional neural network to localize characters, resulting in long processing latency in detection [Wang et al., 2012]. On the other hand, the word-level method [Jaderberg et al., 2014a] has shorter inference time but large memory consumption due to the huge size of the fully-connected layer.

For a real-time NSTP application targeted for ADAS, one needs a method with memory efficiency, fast processing time as well as low power. Recent advancement in binary-constrained deep learning [Courbariaux and Bengio, 2016] has opened up new opportunities for highly efficient CNN realization for the real-time NSTP. In this paper, we propose a binary convolutional encoder-decoder network (B-CEDNet) that can perform a real-time one-shot text interpretation. Instead of detecting characters sequentially [Bissacco et al., 2013, Wang et al., 2012, Shi et al., 2015], our proposed network detects
multiple characters simultaneously. It can distinguish different classes of characters and recovers their spatial and morphologic information by one forward pass. The output is a set of salience maps with the same size as the input image, indicating pixel-wise posterior probability distribution over a category space that composes 26-character and a background class, which allows paralleled character prediction with significant speedup. More importantly, different from traditional CNN engine, by applying binary constraints in training, it results in a B-CEDNet with massive computing parallelism with binarized weights and activations. The experiment shows that our proposed network achieves up to 91% pixel-wise accuracy on public dataset Lucas et al. [2003], Karatzas et al. [2013]. Furthermore, we observe an impressive 4.59 ms average forward time for processing a $32 \times 128$ grayscale scene text image with a small network size of 2.14 MB, which has up to 8 times faster run-time and 96% smaller memory usage than its full-precision version.

## 2 B-CEDNet architecture

The conventional NSTP architecture [Bissacco et al. 2013] ignores the spatial information of features, which leads to a slow sequential character detection. In contrast, the proposed B-CEDNet shown in Figure 1 makes use of deconvolution techniques [Badrinarayanan et al. 2015] to recover this spatial information, allowing paralleled character processing. Specifically, it takes a $32 \times 128$ grayscale image as input and converts it to a compact high-level feature, which is further decoded into a set of salience maps that indicate the categorical, spatial and morphologic information of the characters.

The B-CEDNet consists of three main modules, adapter module, binary encoder module and binary decoder module. The adapter module (block-0) contains a full-precision convolutional layer, followed by a batch-normalization (BN) layer and binarization (Binrz) layer. It transforms the input data into binary format before feeding the data into binary encoder module. The binary encoder module consists of 4 blocks (block-1 to -4), each of which has one binary convolutional (BinConv) layer, one batch-normalization (BN) layer, one pooling layer and one binarization (Binrz) layer. The BinConv layer takes binary feature maps $a^b_{k-1} \in \{0, 1\}^{W_{k-1} \times H_{k-1} \times D_{k-1}}$ as input and performs binarized convolution operation which is illustrated as follows:

$$s_k(x, y, z) = \sum_{i=1}^{w_k} \sum_{j=1}^{h_k} \sum_{l=1}^{d_k} XNOR(w_k^b(i, j, l, z), a^b_{k-1}(i + x - 1, j + y - 1, l)), \quad (1)$$

where $XNOR(\cdot)$ is defined as bit-wise XNOR operation, $w_k \in \{0, 1\}^{w_k \times h_k \times d_k}$ are the weights in $k$-th block and $s_k \in \mathbb{R}^{W_k \times H_k \times D_k}$ is the output of the spatial convolution. Then $s_k$ is normalized by the BN layer before pooling and binarization. The output of $k$-th BN layer $a_k \in \mathbb{R}^{W_k \times H_k \times D_k}$ is represented by

$$a_k(x, y, z) = \frac{s_k(x, y, z) - \mu(x, y, z)}{\sqrt{\sigma^2(x, y, z) + \epsilon}} \gamma(x, y, z) + \beta(x, y, z), \quad (2)$$

where $\mu$ and $\sigma^2$ are the expectation and variance over the mini-batch, while $\gamma$ and $\beta$ are learnable parameters [Ioffe and Szegedy 2015]. The output of the BN layer is subsequently down-sampled by the pooling layer. Here we apply $2 \times 2$ max-pooling to filter out the strongest response which will be binarized by the Binrz layer. The binarized activations $a^b_k$ of $k$-th block can be represented as

$$a^b_k(x, y, z) = \begin{cases} 0, & a_k(x, y, z) \leq 0 \\ 1, & a_k(x, y, z) > 0 \end{cases} \quad (3)$$

What is more for the decoder module, it translates the compact high-level representation $a^b_k \in \{0, 1\}^{2 \times 8 \times 512}$ generated by the encoder into a set of salience maps $p \in \mathbb{R}^{32 \times 128 \times 27}$ that indicates the spatial probability distribution over category space including 26 characters and a background class. The decoder module is composed of 6 convolutional blocks (block-5 to -10). Block-5 to -8 are formed by one un-pooling layer, one BinConv layer, one BN layer and one Binrz layer. Note that there exists a symmetric structure along block-1 to -8. Thus the un-pooling layers [Badrinarayanan et al. 2015] within block-5 to -8 simply assign the input pixels back to their original position according to the index generated by the corresponding max-pooling layer and pad the remains with zeros. The up-sampled feature maps then go through the binary convolution, normalization and binarization. The output of block-8 is a $32 \times 128 \times 512$ tensor which will be processed by block-9 and -10 to generate spatial salience map. Block-9 and -10 form a 2-D spatial classifier with $1 \times 1$ convolution window and softmax output. It produces the posterior probability distribution over the category space for each pixel in the original image.
Figure 1: (a) Conventional architecture of NSTP system; (b) Proposed B-CEDNet NSTP system.

3 Training

The B-CEDNet can be trained and optimized under binary constraints proposed in [Courbariaux and Bengio, 2016], which can significantly reduce memory usage and also improve parallelism. In the existing binary CNN method [Courbariaux and Bengio, 2016], hinge loss function is used for training, which is however unsuitable for our application because it fails to provide a probability interpretation from the input image. In this paper, we apply cross-entropy error as the loss function by removing the Binrz layer in block-10. For our application, the prediction error $J$ is represented as follows:

$$J(w) = \frac{1}{N \cdot W_{10} \cdot H_{10}} \sum_{i=1}^{N} \sum_{m=1}^{W_{10}} \sum_{n=1}^{H_{10}} \sum_{c=1}^{C} \{Y(i)(x, y) = c\} \ln \frac{e^{a_{i10}(m, n, c)}}{\sum_{c=1}^{C} e^{a_{i10}(m, n, c)}}, \quad (4)$$

where $N$ is the number of training samples in a mini-batch, $C$ is the number of classes, $w$ is the filter weights, $Y(i) \in \{1, ..., C\}^{H_{10} \times W_{10}}$ is the 2-D label of $i$-th training image, $a_{10} \in \mathbb{R}^{H_{10} \times W_{10} \times C}$ is the output of the BN layer in block-10.

To achieve generality of trained model, it usually needs a large amount of labeled data for training. However, the existing datasets are limited to word-level annotation [Veit et al., 2016] or cannot provide enough pixel-wise labeled data [Karatzas et al., 2013]. Inspired by Jaderberg et al. [2014a], we create a text rendering engine that generates texts with different fonts, colors and projective distortions. The labeled image has the same size with the corresponding text image and provides a pixel-wise labeling over the category space. Additionally, our model is trained by AdaMax optimizer [Kingma and Ba, 2014] with initial learning rate of 0.002, learning rate decay of 0.9 and mini-batch size of 20.

4 Experiment results and discussion

4.1 Experiment setup

The model is built based on MatConvNet [Vedaldi and Lenc, 2015] on Dell Precision T7500 server with Intel Xeon 5600 processor, 64GB memory and TITAN X GPU. To evaluate the performance, we train the model on synthesis scene text dataset with 200,000 images and test it on the standard datasets ICDAR-03 and ICDAR-13 [Lucas et al., 2003, Karatzas et al., 2013].

4.2 Pixel-wise accuracy

Table 1 reports the pixel-wise accuracy on the testing datasets mentioned above. We achieve notable 90% and 91% pixel-accuracy on ICDAR-03 and ICDAR-13. Figure 2 (a) shows the ideal cases, where our binary model is capable to precisely recognize each character and recover their outline information under normal contrast and even illumination condition. While, in the non-ideal cases, the salience maps produce low confidence value in the area with uneven illumination or low contrast as shown in Figure 2 (b). It indicates that the model feels confused (unconfident) when interpreting the characters. It is worth noting that the robustness can be improved by extending the training set to include the missed cases. Therefore we believe B-CEDNet will be promising in fast scene text detection and natural text interpretation.

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1 In the proposed network $C$, $H_{10}$, $W_{10}$ are 27, 32 and 128, respectively.
Table 1: Pixel-wise accuracy of our proposed network on ICDAR-03 and ICDAR-13.

|          | ICDAR-03 | ICDAR-13 |
|----------|----------|----------|
| Binary   | 0.90     | 0.91     |
| Non-binary | 0.90    | 0.91     |

Figure 2: (a) Testing samples with high prediction accuracy rate; (b) Testing samples with low prediction accuracy rate.

4.3 Run-time and memory usage

Figure 3 compares the inference time for B-CEDNet running on baseline kernel and XNOR kernel [Courbariaux and Bengio 2016]. Baseline kernel is an optimized matrix multiplication kernel, while the XNOR kernel is tailored for bit-count operation in binary network. We measure the inference time with a batch of input images (size of 16) to obtain higher utilization of GPU. Due to the bit-count operation and huge memory access reduction, the B-CEDNet achieves an average of 4.59 ms inference time and 8× speedup with XNOR kernel on TITAN X GPU compared with baseline kernel. Since XNOR kernel introduces run-time overhead concatenating 32 binary values into a 32-bit register, the speedup is more remarkable when the convolutional operation becomes more intensive. Accordingly, the most computation-intensive block, block-8 has the highest speedup of 17.7×. On the other hand, the memory usage is reduced by over 96% (2.14 MB) compared with the full-precision version (66.12 MB).

Figure 3: Inference run-time and memory consumption of B-CEDNet and its full-precision version.

5 Conclusion

In this paper, we have developed a binary convolutional encoder-decoder network (B-CEDNet) for real-time NSTP applications. The B-CEDNet can effectively capture the categorical, spatial and morphologic information from the text image and is extremely computationally efficient with binary weights and activations trained from binary constraints. By training with over 200,000 synthesis scene text image, it can achieve up to 91% pixel-wise accuracy. It only consumes 4.59 ms inference time realized on GPU with a small network size of 2.14 MB, which is up to 8× faster and 96% smaller than its non-binary version.
References

Vijay Badrinarayanan, Alex Kendall, and Roberto Cipolla. Segnet: A deep convolutional encoder-decoder architecture for image segmentation. *arXiv preprint arXiv:1511.00561*, 2015.

Alessandro Bissacco, Mark Cummins, Yuval Netzer, and Hartmut Neven. Photoocr: Reading text in uncontrolled conditions. In *Proceedings of the IEEE International Conference on Computer Vision*, pages 785–792, 2013.

Gobinda G Chowdhury. Natural language processing. *Annual review of information science and technology*, 37(1):51–89, 2003.

Matthieu Courbariaux and Yoshua Bengio. Binarynet: Training deep neural networks with weights and activations constrained to+ 1 or-1. *arXiv preprint arXiv:1602.02830*, 2016.

Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*, 2015.

Max Jaderberg, Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman. Synthetic data and artificial neural networks for natural scene text recognition. *arXiv preprint arXiv:1406.2227*, 2014a.

Max Jaderberg, Andrea Vedaldi, and Andrew Zisserman. Deep features for text spotting. In *European conference on computer vision*, pages 512–528. Springer, 2014b.

Dimosthenis Karatzas, Faisal Shafait, Seiichi Uchida, Masakazu Iwamura, Lluis Gomez i Bigorda, Sergi Robles Mestre, Joan Mas, David Fernandez Mota, Jon Almazan Almazan, and Lluis Pere de las Heras. Icdar 2013 robust reading competition. In *2013 12th International Conference on Document Analysis and Recognition*, pages 1484–1493. IEEE, 2013.

Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, pages 1097–1105, 2012.

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

Simon M Lucas, Alex Panaretos, Luis Sosa, Anthony Tang, Shirley Wong, and Robert Young. Icdar 2003 robust reading competitions. In *ICDAR*, volume 2003, page 682. Citeseer, 2003.

Baoguang Shi, Xiang Bai, and Cong Yao. An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition. *arXiv preprint arXiv:1507.05717*, 2015.

A. Vedaldi and K. Lenc. Matconvnet – convolutional neural networks for matlab. In *Proceeding of the ACM Int. Conf. on Multimedia*, 2015.

Andreas Veit, Tomas Matera, Lukas Neumann, Jiri Matas, and Serge Belongie. Coco-text: Dataset and benchmark for text detection and recognition in natural images. In *arXiv preprint arXiv:1601.07140*, 2016. URL http://vision.cornell.edu/se3/wp-content/uploads/2016/01/1601.07140v1.pdf.

Tao Wang, David J Wu, Adam Coates, and Andrew Y Ng. End-to-end text recognition with convolutional neural networks. In *Pattern Recognition (ICPR), 2012 21st International Conference on*, pages 3304–3308. IEEE, 2012.