Robust Deep Learning-Based Barcode Detection

Xiaoyan Dai, Yisan Hsieh

Abstract—Barcode processing of seized images is quite a big challenge, as different shooting conditions can result in different barcode appearances. In this paper, we design a robust barcode "scanning" system by applying deep learning. In order to improve barcode detection performance of deep learning model, we propose synthetic-to-real data augmentation to generate various data closed to real scene. Comparisons with previous works and evaluations with our original data set show that the proposed approach achieves state-of-the-art performance both in normal images and difficult images in the real-world scenario. In addition, the system is designed to use low-resolution image for barcode detection and high-resolution partial image for barcode recognition, which is and is applicable to real-time applications.

Index Terms—barcode detection, data augmentation, deep learning, image-based processing, barcode scanning, segmentation, distortion.

1 Introduction

A barcode is a method of representing data in a visual, machine-readable form. Barcode is like a unique fingerprint for a product and is usually printed on the item itself or on its packaging. It is a set of parallel vertical lines of varying thickness and sizes containing data used for informational and marketing purposes as well as for tracking products throughout their lifecycle. There are various types of barcodes in use today such as Code 128, Code 39, EAN and so on [1].

Optical barcode scanner is widely used to read barcode information and store them to a computer system for process. It usually consists of three different parts including illumination system, sensor and decoder. In general, a barcode scanner detects black and white elements of barcode by illuminating the code with a red light, which is then converted into matching text. In point of sale (POS) systems of supermarket, stationary barcode scanners and hand hold barcode scanners are used to pull product info and add it to checkout total to automate the checkout process.

Recently, image-based barcode “scanning” system has been proposed. The system uses a webcam, digital camera or smart device to capture an image or video stream and extract barcode information. There are three major advantages of image-based barcode “scanning”. The cost of the camera is low, the distance from the camera to the “scan” target is not strictly restricted, and it is possible to provide a generic solution supporting a variety of barcode formats. Therefore, the image-based system has a future prospect for automatic identification field to increase productivity [2], [3], [4]. However, barcode processing of seized images is quite a big challenge because the appearance of the barcode images may differ from the ideal due to various shooting conditions such as lighting, distortion, angle, distance, and target package.

This paper proposes an image-based barcode detection and recognition approach using captured input. We aim to detect and recognize barcodes printed on moving products at high speed and accuracy. This enhances the convenience of current POS systems that need to orient barcodes towards barcode scanners.

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2 Related Works

Existing approaches to barcode detection are either geometrical-based or deep learning-based. Different approaches based on geometrical features are proposed. Normand et al. [5] and Viard-Gaudin et al. [6] search for groups of lines with mono-oriented gradients to locate barcodes region. Muniz et al. [7], Youssef et al. [8] use Hough transformation for skew detection and contour tracing. Arnould et al. [9] use morphological filters to extract barcode lines against orientation and size. Raskar et al. [10] propose a de-convolution method to locate barcodes by removing motion blur. Kutiyanawala et al. [11] apply multichannel Gabor filtering technique to extract texture features for multi-resolution analysis. Even though these methods are effective in locating barcodes under certain conditions, they involve manual work, making them more complex and inefficient, especially when dealing with massive amounts of data. The task of detecting barcodes under complex conditions is challenging, especially with large amounts of data to achieve high accuracy.

With the development of deep learning, deep-based methods have also been applied. Ren et al. [12] adopt Faster R-CNN to improve the accuracy of clear background barcode detection. Xia [13] uses a deep learning-based detector of You Only Look Once to design a barcode recognition system. Hansen et al. [14] use an object detection network to locate barcodes and another subsequent network to predict the rotation angle of the barcode in the bounding box region. Li et al. [15] integrate Faster R-CNN with Maximally Stable Extremal Region and Adaptive Manifold filter to detect barcodes under background noise.

These deep-based methods offer effective solutions for barcode detection of large quantities of data with the help of data augmentation techniques used to obtain more representative training data. Typically, the data augmentation process first collects barcode samples and then adjusts common data expansion factors such as degree of brightness, angle of rotation, and scaling to provide a training data set for deep learning models. It is well known that small data sets usually cause poor performance of deep learning models, but big data sets have high costs for data acquisition and manual labeling. Therefore, an effective data augmentation approach is important for training deep learning models.

This paper proposes a robust barcode processing approach that is useful for POS systems. We first propose a deep-based barcode detection approach using a synthetic-to-real data augmentation strategy, and then apply online open source Pyzbar, a Python package developed by Lawrence Hudson for barcode recognition. Our experiments verify that the proposed synthetic-to-real data augmentation achieves coexistence of both data collection cost and data volume and data quality for deep learning models training. The deep-based barcode detection method enhances the identification of barcodes with different distortions, lighting, resolutions, backgrounds, etc. Currently, we use a webcam or digital camera to get the images, this algorithm can be implemented on smart devices as well. This technique can also be used for inventory and any other uses other than POS system. The remainder of the paper is organized as follows: Section 3 presents the proposed barcode detection technique. Section 4 demonstrates the effectiveness of the proposed method through extensive experiments. Section 5 draws conclusions.

3 Our Approach

In this section, we explain in the order of deep learning network adopted for barcode detection, the proposed architecture design of barcode “scanning” system, and the proposed synthetic-to-real data augmentation for deep learning models training.

3.1 YOLACT Algorithm

YOLACT, short for "You Only Look At Coefficients", is a deep learning network for achieving real-time instance segmentation [16]. It is a one-stage algorithm performing instance of mask producing and object detection independently. It can achieve 29.8 mAP on MS COCO at 33.5 fps, which is faster than any previous approaches. The linear combination of mask coefficients produces high-quality masks and stable detection results as well. We adopt the network and modify it for barcode detection.

3.2 System Architecture Design

The system architecture is designed as shown in Fig. 1. We first reduce the resolution of the camera input, then use the YOLACT algorithm to detect the barcode in the low-resolution image and get the bounding box and segmentation mask of it. We next use the mask information and the original image to get a high-resolution partial image containing the barcode. We finally apply the open-source Python package to perform barcode recognition in the mask region and output decoded information.

The area outside the barcode takes unnecessary computational cost, especially when processing high-resolution input image, which makes detection not suitable for real-time applications. However, as introduced on the previous page, since the recognition object may not be placed near the camera, the resolution maybe low and the accuracy of barcode recognition may be reduced. Our strategy aims to effectively maintain a balance between processing speed and cognitive performance. We use low resolution for barcode detection to reduce the cost of the detection process and high-resolution barcode trimming region to improve the accuracy of barcode recognition.

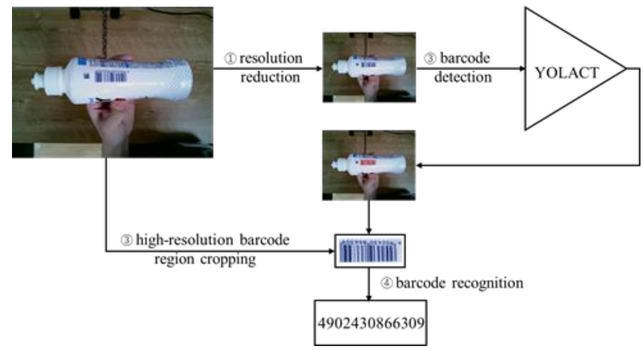

Fig. 1. System design of barcode “Scanning”

3.3 Synthetic-to-Real Data Augmentation

Training deep learning models requires large amounts of data with ground truth. In order to save time and effort in real data collection and ground truth labelling, we incorporate computer process-generated barcode data. When generating barcodes with the computer process, the ground truth labels are also generated automatically, so no manual work is required. However, the generated barcodes may not be useful when directly used for training, as they miss various conditions commonly found in actual barcode images, such as distortions, reflections, blur, lighting, etc. Therefore, direct use of the synthetic data can cause them to be unsuitable for training purposes and can even cause overfitting of deep learning models. Our proposal is an effective solution for creating data sets that take into account optimal conditions for enhancing training data and improve barcode detection performance.

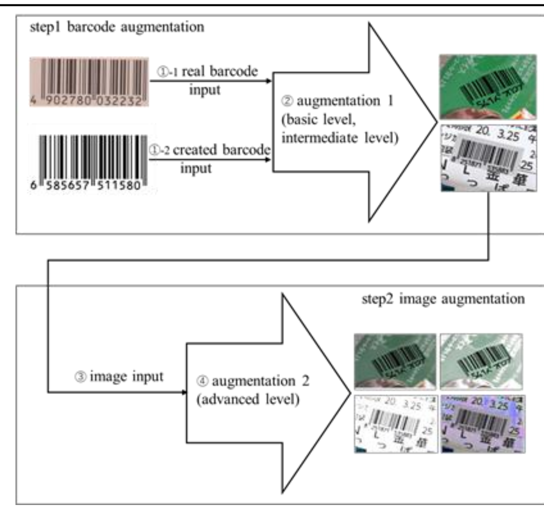

Fig. 2. Processing flow of data augmentation

The data augmentation is composed of two steps (Fig. 2). We first augment barcodes themselves to generate a wide variety of barcode data that is close to the objective states of the real world, and then augment images containing the barcodes to generate a large variety of image data that is close to the actual shooting environment.

The first step, barcode augmentation, is to augment both the collected barcodes and the generated barcodes. This process consists of basic augmentation and intermediate augmentation. The basic augmentation is the usual augmentation process for generating different barcodes, such as rotating at different angles, horizontal/vertical flips, random cropping, and changing aspect ratios.

Intermediate augmentation is our unique approach to make the barcode data reproducible as it is processed in the actual scene. Since we are aiming for a barcode "scanning" system for super-market, we need to consider the various states of the barcodes printed on the products. Here we give some examples of real barcodes. In Fig. 3, (a) shows clear barcode samples generated by the computer process, and (b)~(g) show the actual barcode samples. (b) shows distortion caused by the shape change of the products' packages, especially in the case of bending of plastic packages or bottles and cans. (c) shows reflections caused by various lighting conditions. (d) shows blur caused by movement of the products. (e) indicates obstruction caused by a hand or something while holding the products. (f) shows barcodes printed on complex backgrounds. (g) shows some samples containing the multiple problems showed above. It is obvious that the actual barcodes are quite different from the synthetic data. We address the problems by applying computer vision technology to extent barcodes and primarily address these issues with intermediate augmentation.

Fig. 3. Barcode samples for intermediate augmentation

The second step, image augmentation, is to augment the images containing the various barcode data generated in the first step. Why do we need the image augmentation? During our experiments, we found that lighting conditions had a significant impact on the performance of barcode detection, making it difficult to identify barcodes in response to changes in hue, contrast or color temperature. Therefore, we propose advanced augmentation as another strategy. We adjust contrast, brightness, and color shift control for the images that contain the barcode data. Also, the reason why we execute image augmentation by image instead of the barcode itself is that it is natural that not only the barcode but the entire image including the barcode has the same lighting condition. Here we show some image samples including barcodes. In Fig. 4, (a) shows image samples with similar lighting conditions, and (b) shows some samples with different lighting conditions.

Fig. 4. Image samples of lighting conditions

4 Experiments

In this section, we make some experiments to verify the effectiveness of our approach. We first compare the performance of barcode detection with the previous methods [17], [18], [19], and then verify performance of the proposed approach with our original evaluation data set.

4.1 Experiment 1

The purpose of this experiment is to compare our approach with existing methods.

We use two public data sets for evaluation. The first data set is Muenster Barcode Database, which consists of 1055 EAN and UPC-A barcodes captured on a Nokia N95 phone. The second data set is ArteLab Barcode data set, which contains 365 EAN plain barcodes and 155 difficult barcodes on a variety of cell phones. In this experiment, the image size of both data sets is 640*480.

Evaluation metrics of barcode detection used in the previous methods are Jaccard accuracy and detection rate. Jaccard accuracy is an intersection of detection result and ground truth, and detection rate corresponds to a percentage of images achieving at least T Jaccard accuracy. In this experiment, we adopt detection rate as a metric. The reason why Jaccard accuracy is not used is that the ground truth of the public data is set to be the bounding box of barcodes, while our algorithm outputs an area that contains both barcodes and numbers. For comparison, T is set to 0.5.

We collect the results reported in the articles and compare them with our results. In previous works, some images were used for training, so only partial images were used for evaluation, but we evaluate the complete sets. Table 1 shows the results of comparing the two data sets. Numbers in parentheses

ISSN 2229-5518

indicate the image numbers used for evaluation. We can see that our method has achieved significant improvements in the detection of both data sets. In addition, even on difficult images in ArteLab data set, our approach achieves high detection score.

TABLE 1
RESULTS COMPARISON WITH PUBLIC DATA SETS

Approach	Results of Muenster	Results of ArteLab	
		Plain	Difficult
Zamberletti et al. [17], 2013	0.829 (595)	0.805 (129)	--
Creusot et al. [18], 2015	0.963 (595)	0.893 (365)	--
Namane et al [19], 2017	0.966 (595)	0.930 (365)	--
Ours	0.989 (1055)	0.974 (565)	0.945 (155)

4.2 Experiment 2

The main purpose of this experiment is to investigate effectiveness and robustness of the approach proposed in the real-world scenario.

As mentioned in the previous part, we define challenging barcodes as having distortion, reflection, blur, ambient lighting, etc. Since there is currently no such data set, we build our own assessment data that includes these difficult states. In addition to general products, we also collect products with natural soft packing that cause distortion, and shoot at different shooting angles and lighting conditions in order to reproduce perspective, reflection, hue, etc. In this experiment, we also use the matric of detection rate for evaluation.

In order to verify whether our proposed approach can overcome each harsh condition, we divide the evaluation data set into each major challenge and output each barcode detection performance. We divide the barcode detection challenges into two levels. Normal level includes images that have no or some minor challenges. Difficult level includes images with one of the severe challenges. The evaluation data set contains some images that are more difficult than the samples shown in Fig. 3.

Table 2 shows the barcode detection results using the original data set. We achieve good detection performance on each challenge. In Fig. 5, (a) shows some image samples that have successfully detected barcodes. (b) shows the detection results of (a). Here the barcode bounding box is marked with a red rectangle and the mask is filled with red. (c) indicates some images failed to be referenced. Since the image resolution of barcode detection is 640*480, detection failures mainly occur in very small and complex images.

TABLE 2
RESULTS OF BARCODE DETECTION WITH OUR ORIGINAL DATA SET

Difficulty level	Challenge	Number of images	Detection rate
normal	without or with mild challenge	351	0.970
difficult	distortion	417	0.970
	reflection	203	0.936
	blurring	189	0.980
	lighting	102	1.00
	others (occlusion, backgrounds, etc.)	104	0.990
	total	1366	0.968

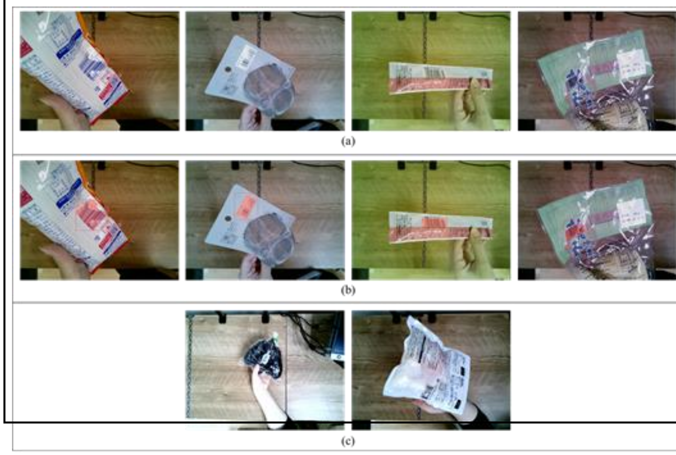

Fig.5. Samples of barcode detection

The results of these experiments show that the proposed approach performs well for both normal and difficult images. Even though some images may have serious distortions, reflections or multiple problems, it is possible to detect barcodes by applying our approach to each frame and merging the results of multiple moving frames.

Fig. 6 shows a comparison of barcode detection WITH and WITHOUT the proposed data augmentation. The latter refers to the basic level data augmentation described in the previous part. Obviously, our approach will significantly improve the performance of barcode detection.

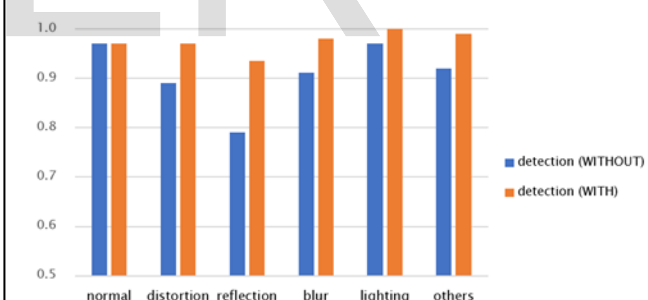

Fig.6. Barcode detection comparison of WITH and WITHOUT the proposed augmentation

In addition, we verify that our proposed system using hybrid resolution is suitable for barcode recognition.

5 CONCLUSIONS

In this work, we propose a robust deep-based barcode detection using synthetic-to-real data augmentation. We adopt the YOLACT object detection network to locate barcodes. In order to improve the training performance of deep learning models, we propose a novel data augmentation approach to generate various data that are close to the actual scene. We incorporate the actual barcodes into the barcodes generated by the computer process to save the cost and effort of data collection and labeling. The data augmentation consists of two steps. The first step is to augment the barcodes with different statuses such as distortion, blur, complex background, etc. The second step augment images containing the barcodes generated in the first step of various real lighting conditions. Comparisons with previous works shows improvement in barcode detection with our proposed approach. In addition, the evaluation using our original data set with more difficult images validates it effectiveness and robustness.

The experiments have shown that barcode detection with the proposed data augmentation approach achieves state-of-the-art performance in both normal and difficult images. In addition, the system designed to use low-resolution image for barcode detection and high-resolution partial images for barcode recognition achieves in both speed and performance. This approach enjoys practicability, accuracy, and speed. We believe our approach is useful and applicable in the field of automatic identification to improve productivity.

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