Video Text Detection and Recognition for Marketing using Deep Learning Technique

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Abstract— Marketing analytics is the practice of managing and studying metrics data in order to determine the ROI of marketing efforts like calls-to-action (CTAs), blog posts, channel performance, and thought leadership pieces, and to identify opportunities for improvement. By tracking and reporting on business performance data, diagnostic metrics, and leading indicator metrics, marketers will be able to provide answers to the analytics questions that are most vital to their stakeholders. In this paper, we propose a novel method that transferred deep convolutional neural networks for detecting and recognizing video text. We partition the candidate text regions into candidate text lines by projection analysis using two alternative methods. We develop a novel fuzzy c-means clustering-based separation algorithm to obtain a clean text layer from complex backgrounds so that the text is correctly recognized by commercial optical character recognition software. The proposed method is robust and has good performance on video text detection and recognition, which was evaluated on three publicly available test data sets and on the high-resolution test data set we constructed.

Keywords— Video Text Detection, Recognition, Transferred convolutional neural network, Fuzzy c-means Clustering

I. INTRODUCTION

Regardless of business size, marketing analytics can provide invaluable data that can help drive growth. Enterprise marketers at first may find the process too complicated, while small and mid-sized business (SMB) marketers assume a company of their size won't benefit from implementing metrics, but neither perception is true. As long as marketing analytics is carefully curated and properly implemented, the data collected can help a business of any size grow.

With proper marketing metrics and analytics in place, marketers can better understand big-picture marketing trends, determine which programs worked and why, monitor trends over time, thoroughly understand the ROI of each program, and forecast future results. With 78% of B2B marketing executives currently measuring the impact of their marketing programs on revenue, it's clear that more businesses are getting on board with marketing analytics, even if they were a bit hesitant before.

“Too often marketers talk about activities instead of outcomes—for example, how many campaigns they ran, how many trade shows they participated in, how many new names they added to the lead database. These are metrics that reinforce the perception that marketing is a cost center, not a revenue driver.”

Thus, video text detection and recognition are significant and challenging tasks because of variations in languages, fonts, and complex backgrounds [3]. Generally speaking, video text can be classified into scene text and artificial text [4]. Of these, the latter usually concisely depicts important video content. For instance, captions in news videos usually describe event information, and subtitles in speech videos usually provide core ideas. Thus, in this paper, we focus on the detection and recognition of artificial text in video frames. Video OCR technology [5] generally has similar processing steps, including text detection, localization, extraction, and recognition. The detection step aims to find text regions; the localization step concentrates on the accurate position of text lines.

First, it is difficult to identify text regions accurately and completely because of various languages, fonts, resolutions, and particularly complex backgrounds. For example, edge-based approaches may produce many false positives when the complex background also has a high density of edges. Second, the heuristic constraints and machine learning methods proposed to eliminate false positives for video text are always optimized for specific situations, which reduce the generalizability of these methods. In fact, no matter what the language and font the text has, the component characters are always formed by crosses of strokes in limited space. Therefore, many corners exist [6]. CNNs can learn discriminative features for precise classifications directly from a large amount of diverse raw data. Transfer learning can transfer the knowledge from one specific task to relevant tasks with good performance.

II. TRADITIONAL METHODS FOR TEXT DETECTION

A large number of techniques have been developed by various researches for text detection and recognition in natural scene images. All these techniques are roughly classified into three basic techniques in figure 1:

Texture Based Method: This method uses the texture based properties such as Fourier transform, local intensity, filter response and wavelet coefficients for distinguishing the text part and non-text part from the natural images. Region Based

Method: This method uses the properties like color, intensity and edge similarity for distinguish the text and non-text part in natural images. It is categorized into three types:

Edge Based: - this method used the edge detector operator to detect the edges of the images. Usually, two types of edge detection methods are applied such as canny and Soble edge operator.

Connected Component Based:- In this method, character components are identified using clustering and edge detection methods. Maximum Stable Extremal Region is one of the major techniques of this method.

Stroke Width: - In this method, text features can be identified through stroke of the components. Character components having constant strokes are treated as text and remaining are treated as non-text. Stroke width transform operator is used for this operation in text detection.

Hybrid Method: To overcome the limitations of all the above mentioned techniques, the combination of two or more techniques is used known as hybrid technique.

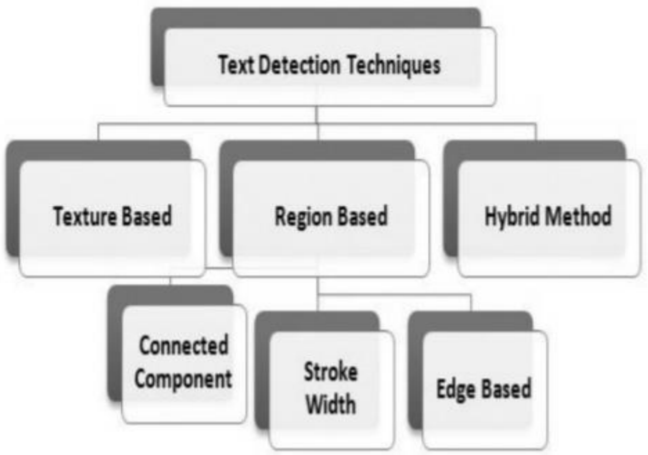

Figure 1: Various types of Text Detection Techniques

Table I: Describes the Advantages and Disadvantages of Traditional Text Detection Methods

Text Detection Methods	Advantages	Disadvantages
Texture based Method	Can easily handle the noisy image	High computing complexity. Fails in multi orientation text
Region based method • Component Connected method • Stroke Based • Maximum Stable Extremal Region	• Easily handle natural scene images • Low computational cost • Handle the multi-oriented text	• Fails to detect on light variations text images • Very sensitive to noisy images
Hybrid Method	surmount the drawbacks of texture based method and region based method	Complex in implementation

III. DEEP LEARNING IN TEXT DETECTION

In the recent years, due to the increased popularity of deep learning techniques, the use of this technique has become trendy for the task of computer vision and pattern recognition problem in natural scene images. Now a days, many researchers are adopting the deep learning technique for text detection in natural scene images such as conventional neural network, recurrent neural network, fully conventional network, feed forward back propagation neural network. The basic functioning of the convolutional neural network is explained in figure 2.

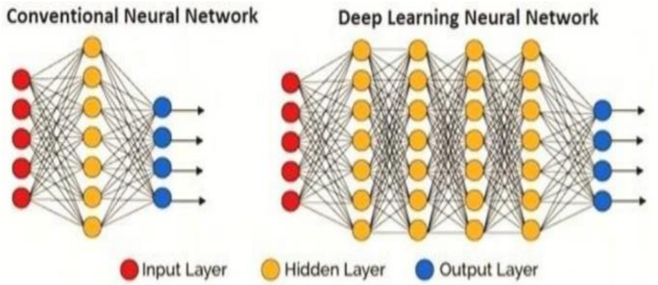

Figure 2: Depicts the architecture of conventional neural network and deep learning neural network

Before 2016, in scene text detection method, the character candidates were identified using hand-craft features. The Convolutional Neural Network/Random forest was used to discriminate the Text / non-text part and to eliminate the false positive in natural images. After 2016, segmentation based method; proposal-based method and hybrid method are used for text detection in natural scene images.

Deep neural network is a term which is widely used these days, consists of multiple hidden layers as compared to simple neural network as shown in figure 3. So, this is the basic reason that the deep learning neural network provides more accurate results as compared to that of simple neural network.

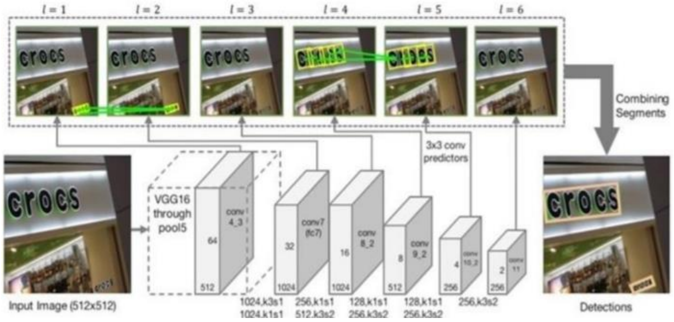

Figure 3: Explains the Deep Neural Network Architecture

IV. PIPELINE PROCESS FOR TEXT EXTRACTION

The overall system for text extraction involves the various steps and the accurateness of every step is mandatory for the accurate text detection. In the process of text detection, the location of detected text is identified using various techniques. Then the identified text needs to get separated from non-text region of the natural scene image. Mainly the pipeline process for text extraction consists of following steps:-

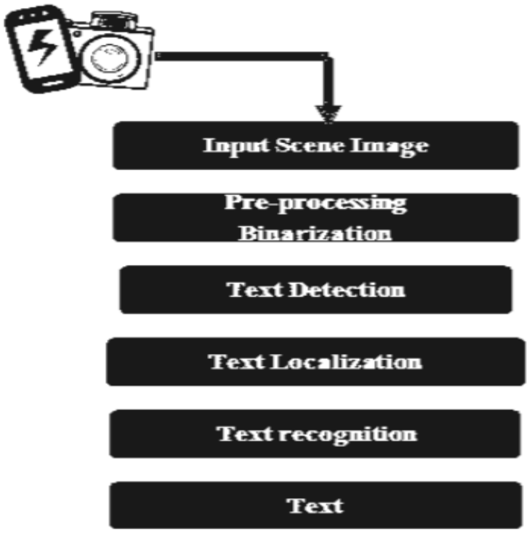

Figure 4: Describes the various steps involved in text extraction

The accuracy of any text extraction technique depends upon the accuracy of text detection technique. So, the text detection in natural images has become significant area of research these days. Here we describe the various steps of text detection applied on real time image.

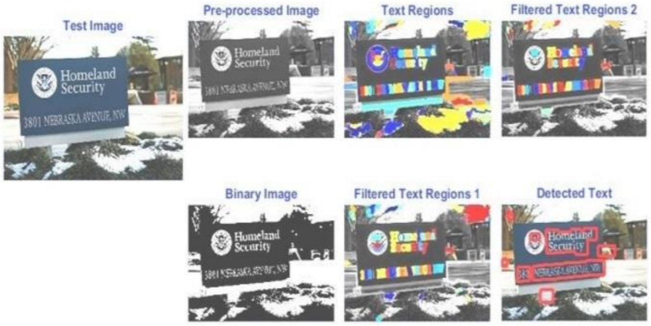

Figure 5: Depicts the pipeline process for text detection in natural scene images

V. PROPOSED METHODOLOGY

The proposed approach is composed of four steps: video decoding, text detection, candidate text line localization, and false text line elimination using a deep learning method. First, we utilize the OpenCV library to decode video into frames. Next, we use a corner response feature map detector to obtain candidate text regions. Because there may be multiple text lines in the candidate text region, we then further partition the candidate text lines using two alternative methods. For the first method, candidate text lines are partitioned through projection analysis onto the contours of candidate text regions. If the first method fails, we use a more complicated method, which employs an FCM-based separation method to extract the candidate text layer, converts it to the gray-scale image, and conducts the projection analysis to partition the candidate text lines. In the last step, false text lines are removed by our constructed transferred deep CNN classifiers. The true text lines then undergo FCM-based separation, Otsu binarization, and morphological restoration to obtain OCR-ready binary text. Figure 4 shows the flowchart for the proposed method.

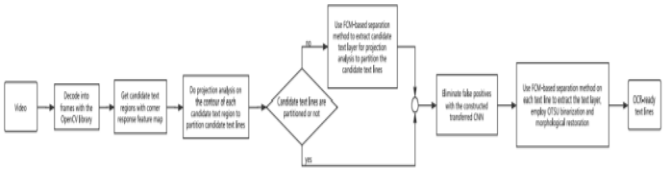
Video
Decode into frames with the OpenCV library
Get candidate text regions with corner response feature map
Do projection analysis on the contour of each candidate text region to partition candidate text lines
Candidate text lines are partitioned or not
no
yes
Use FCM-based separation method to extract candidate text layer for projection analysis to partition the candidate text lines
Eliminate false positives with the constructed transferred CNN
Use FCM-based separation method on each text line to extract the text layer, employ OTSU binarization and morphological restoration
OCR-ready text lines

Figure 6: Flowchart for the proposed method

Corner Response Feature Map

Text in videos always provides supplemental information with good readability (especially the captions). The crosses of strokes in characters cause the generation of many corners.

Video text always has a regular distribution of corner points, which the background generally does not have. Compared with other features, such as edge feature, corners are more stable and robust. The detailed mathematical derivation about corners was presented in. Given a gray-scale image *I*, we take an image patch over the window *W*(*x*; *y*), shift it by (u,v), and calculate the change produced by the shift as follows:

$$E(u,v) = \sum_{W} [I(x+u, y+v) - I(x,y)]^2. \tag{1}$$

The first-order Taylor expansion after omitting the Peano remainder term is used to approximate the shifted image as follows:

$$I(x+u, y+v) \approx I(x,y) + \begin{bmatrix} I_x(x,y) & I_y(x,y) \end{bmatrix} \begin{bmatrix} u & v \end{bmatrix}^T \tag{2}$$

Where *Ix* and *Iy* denote first-order partial derivatives in *x* and *y* directions, respectively, substituting approximation (2) into (1) yields:

$$E(u,v) = \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} \tag{3}$$

Where *M* is the following Hessian matrix:

$$M = \begin{bmatrix} \sum_{W} (I_x(x,y))^2 & \sum_{W} I_x(x,y) I_y(x,y) \\ \sum_{W} I_x(x,y) I_y(x,y) & \sum_{W} (I_y(x,y))^2 \end{bmatrix} \tag{4}$$

If the two eigenvalues of *M* are large and distinct positive values, a shift in any direction will cause a significant increase, and a corner can be determined.

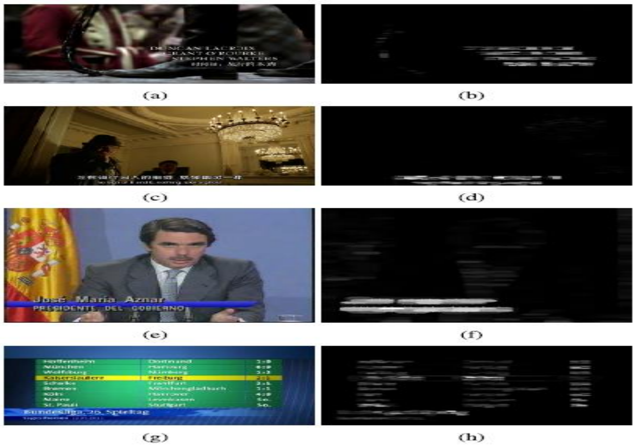

Figure 7: Sample video frames and corresponding CRMs after gray-scale morphological processing

Text Detection

OpenCV is an open-source computer vision library that can be used to process videos and images. First, we use it to decode the video into frames through the cvQueryFrame function. Considering human visual characteristics, the video texts always last at least 2 seconds. Therefore, we grab one frame per second for video text detection so that no video text is missed.

We obtain the CRM of original frame according to (4). Regions of higher brightness always correspond to video texts. We then apply a series of gray-scale morphological operations to enhance the text regions and suppress the non-text regions.

A close operation is utilized to remove the dark points that belong to the background in CRM, and then the tophat operation is used to enhance the bright text areas. The combination of the two operations makes the text regions more distinct and complete. The CRMs after gray-scale morphological processing are presented in figure 7.

After the gray-scale morphological processing, Gaussian filtering is used to smooth the CRM, which contributes to the completeness of text regions to be detected. In order to form reasonable candidate text regions, we propose a binarization method with an adaptive threshold.

VI. SIMULATION RESULT

The performance of the proposed method is evaluated using three publicly available test datasets and our proposed test dataset. The three public datasets are the Microsoft common test set, TV news test set, and YouTube test set.

The _rst dataset contains 45 pictures of low resolution and poor quality, which is not up-to-date. The other two datasets contain high-resolution pictures. However, the size of the two datasets is too small to support further research. Our constructed dataset consists of more than 6,000 typical video frames of high resolution and high quality, about 25,000 text lines, and 42,000 negative samples. These frames are collected from various sources, including movies, cartoons, and TV shows. We sampled 2,000 video frames randomly and used them as the proposed test dataset.

We performed our experiments using Python with the Theano backend and CCC with the OpenCV library. The hardware configuration includes an NVIDIA Geforce GTX 1080Ti with 11-GB GPU memory, an AMD Ryzen5 1400@3.20GHz_4 processor with 64-GB RAM. We resized the candidate text line images into the following input sizes: 224×224 for TVGG and TRESNET, 299×299 for TINCEPTION. In our constructed dataset, 2,000 images are randomly chosen as the test data. For the rest of the images, 80% are randomly selected for training, and the remaining 20% are selected for validation. We adopted the pixel-based evaluation method in, and the experimental results are shown in Table II. The results show that our methods achieve good performance on a wide range of videos, and our TVGG based method performs best. Therefore, we chose the TVGG based method to compare with several state-of-the-art methods on three public test sets.

Table II: Experimental results on the proposed test set

Method	Recall	Precision	FI-measure
Our TVGG based Method	0.88	0.83	0.85
Our TRENET based Method	0.88	0.82	0.85
Our TINCEPTION Based Method	0.87	0.82	0.84

VII. CONCLUSION

Marketers can earn the respect of their organizations by taking a professional approach to marketing metrics and analytics by using integrated technology to provide better insights for informing better business decisions. Marketers who invest in measuring and managing performance create more value, achieving 5% better returns on marketing investments and over 7% higher levels of growth performance. By providing a single platform for reporting across all channels, the entire process is simplified. Additionally, we found that across industries and regions, an integrated analytics approach can free up 15 to 20% of marketing spending.

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