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An Extensive Survey on Text Detection and Recognition

Sheetal Garg[1*], Akshatha P S[2], Kavyashree C [3]

[1,2]Department of Computer Science & Engineering, MVJ College of Engineering, Bangalore, India
[3]Department of Computer Science & Engineering, MVJ College of Engineering, Bangalore

[*]Corresponding Author: sheetal.garg@mvjce.edu.in, Tel.: +91-7760573881

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Abstract— This paper analyzes, compares, and contrasts the various methods in text detection and extraction. Existing techniques are categorized as either stepwise or integrated. Text detection and extraction can be categorized into sub-problems including text localization, verification, segmentation and recognition. It gives an elaborate view of the various methods applied for these sub problems. A number of benchmark datasets are discussed in details with their attributes.

Keywords— Text detection, text localization, text recognition, text segmentation, survey

I. INTRODUCTION

In real life enormous applications are based on text extracted from images. Applications of text extraction from images include guiding tourists, visually impaired people, robots, document analysis, detection of vehicle license plate, analysis of article with tables, maps, charts, diagrams, keyword based image search, identification of parts in industrial automation, content based retrieval, name plates, object identification, street signs, text based video indexing, video content analysis, page segmentation, document retrieving, address block location etc. The quality of detection and extraction of text from images depends on the text features such as color, font, size and orientation as well as the location of the probable text regions. Also, camera based images are prone to a number of possible degradations such as blur, uneven lighting, low resolution and contrast which makes it more tough to recognize any text from the background noise. Many people consider Optical Character Recognition as a solution for detection of text. But in real world it is more challenging. The challenges faced by computer vision and pattern recognition based problems are low quality or degraded data. These problems can be overcome by having an advanced computer vision and pattern recognition applications.

When we say text recognition and extraction it is made up of text localization, verification, segmentation, recognition. Some applications need some special support other than detection and recognition. These include text enhancement, detecting text from videos, text which are oriented in different directions, multi lingual text and distorted text.

Rest of the paper is organized as follows, Section I contains the introduction of importance of text in images, Section II describes the, Section III contain the various types of text present in images. Section III gives the various fields of application for text from images. Section IV contain the methodologies for text detection and extraction systems. Section V gives the details of the various datasets used in this system. Section VIII concludes survey work.

II. TEXT FROM IMAGES

Graphics text and Scene text are two basic types of text. Graphics text is nothing but the machine printed text overlaid graphically. It is usually found in captions, sub titles for videos, emails. Scene text is the text which appears on the objects present in the photos. This includes text on sign boards, packages, clothing, hoarding boards, sign boards etc. in natural scenes. Area of interest is scene text. If the basic aim is to capture the text then it is referred as point and shoot text where as if the text has come along with the scene image then it is called as incidental text.

III. APPLICATION

Text in web images and videos has enormous information. Efficient algorithms are needed for detection of scene text and caption text in videos [1].text recognition and extraction of keywords from multimedia resources like web images and videos enhances multimedia retrieval.

In recent days the popularity of mobile devices with high end cameras has increased. With the help of some modules, these mobile devices automatically input name cards [10], whiteboards [40] and slide presentation.[41].

Signs in natural images carry a lot of information. As this text is scene text hence it is more difficult to extract text from such images. But language becomes a hurdle. To overcome it text recognition and extraction is the solution. This extracted text can be given to a translator system for conversion from one language to other [26].

According to world health organization millions of people are either legally blind or visually impaired. Developing systems to assist the blind people to read [3], smart glasses to take the images and convert it to text or voice are needed.

Recognizing text from packages, tags and containers have broad application related to industry automation.

To automate post office services we need to detect the addresses from the envelopes for sorting. Logistic efficiency can be improved by automatically recognizing the container numbers [39]. The automatic geocoding systems must be equipped to recognize the house numbers and text in maps [168]

IV. METHODOLOGY

Two methodologies for complete Text detection and recognition system are: Stepwise and Integrated. In step wise methodology text detection and text recognition systems are separate. In this system to detect and recognize text a feed forward system is used. For integrated methodologies recognition is the basic goal. Here the text detection and localization share their information with the character classification in association with the joint optimization technique. Stepwise methodology is coarse to fine technique. As it is the combination of two steps integration is a problem. Secondly at each step optimization is not possible which leads to error accumulation. For integrated methodologies as the focus is on word detection hence the increase in number for word could significantly decrease the detection and recognition performance.

Important and useful information can be extracted from scene images. Text extraction methods can be categorized into two types: region-based and texture-based based on the features utilized. The important feature of region based method is that they use the color or gray scale properties or their deviations with corresponding properties of the background.

Connected Components and Edge Based are the two sub categories for region based methods. These two sub categories follow a bottom up approach. Here connected components or edges are identified and then they are combined to form boxes that bound the expected text. They work in bottom up fashion by combining smaller units into resultant larger units until all the regions for expected text are identified. They take help of geometrical knowledge to combine all text components so as to separate out non text regions.

Texture Based methods use the knowledge that text has some features that differentiate them from the background. These techniques are based on Gabor filter, Wavelet, FFT etc.

Connected Component Analysis (CCA) fall under the category of graph algorithms. They arrange the cc's as per the color similarity and spatial layout. To analyze the feature difference and to define the text areas, syntactic pattern recognition methods are applied. To fine tune the syntactic rules, CCA is done with statistical models like Ada Boost classifier which considers spatial features pairwise and generate the CCA models. This approach considerably improves the adaptivity.

Sliding Window Classification method classifies the multiscale image windows into positives. These positives are grouped into text regions with morphological operations [16] or graph methods [23]. The simple and flexible training detection architecture is the plus point for this method. When complex classification methods are used and a large number of windows need to be classified, the computation cost increases accordingly.

Text is often present in stable and divergent colors so that it distinguishes it from the background. Under this assumption color features are used to localize text [19]. These methods operate competently but are sensitive to multicolor characters and uneven lighting which reduces the color features.

Jain and Yu [1] applied the early color based text localization methods. They generated color layers by color reduction, obtained CC's by clustering algorithms, connected CCs into text candidates with color similarities and performed component layout analysis.

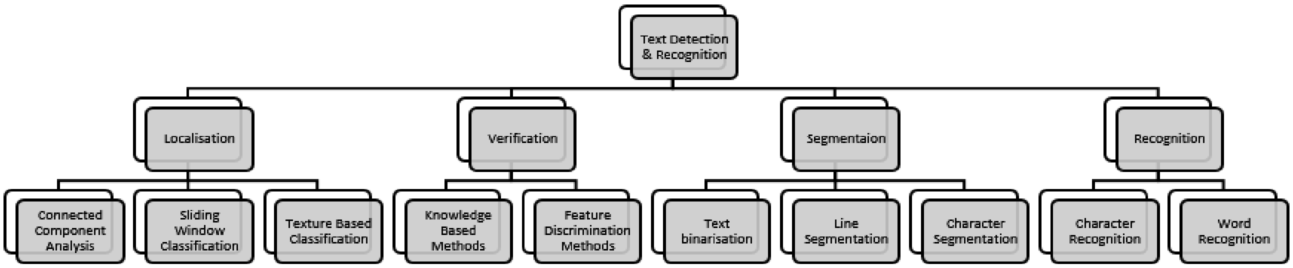

Figure 1 Steps for Text Detection and Classification

In [3] Garcia and Apostolidis used k-means clustering algorithms in HSV color space for text extraction. Karatzas and Antonacopoulos [8] applied Split n Merge strategy in HLS color space to extract text components. Chen et at [6] localized text by Gaussian mixture models in RGB hue.

Text exhibits a strong and symmetric gradient against its background – this is the basis for family of Gradient /Edge based approaches. In [25] edge features are used to detect text components and in [4] gradient features are used.

Sliding Window based text localization is performed by combining color features or gradient/ edge features with ANN [5] or AbaBoost [11]. However complex backgrounds having strong gradient make it difficult to discriminate text components.

Dense characters can be considered as texture [7]. For such features text localization is performed by combining texture features with a multiscale sliding window classification method. Texture features are able to detect dense characters but may fail for sparse characters like signs in scene images.

Li et al. [2] used Wavelet Texture Features for localization. Moseleh et al. [21] improved SWT with the help of Bandlet-based edge detection. This approach can be applied for low resolution text. It enhances text edges and removes noisy edges.

In text regions there is dense presence of corner point. Considering this Haris corners were used to perform localization for videos by Zhao et al. [20]. The author combined corner points into candidates. These were classified by Decision Tree classifier.

The text localization often introduces false positives because a small piece of components / patches may not contain sufficient information for classification. After text localization, holistic features of text regions are available for precise classification and verification.

Prior knowledge about color, size and space consensus, and projection profiles have been used to perform text verification. In [12], the proportion of width and length of minimum bounding rectangles (MBRs), the proportion of text and background pixels in MBRs are used.

Knowledge based verification is simple and intuitive. However, it is difficult to translate prior knowledge of text into well-defined syntactic rules. If the rules are strict, they may fail to keep text that doesn't comply with all the rules. If the rules are loose, they may introduce numerous false detections.

Various features including intensity and shape features [13] and HOG texture descriptors [27], Gabor strokes [24] were used to perform text discrimination. For text discrimination a prerequisite of which is that features extracted from image regions of different aspect ratios are normalized to the same dimensionality. One way to obtain normalized features is to extract global features that are independent of a region aspect ratio. The other is to divide image regions into an equal number of sub-regions of different sizes and extract local features having the same dimensionality from

Ye et al. [9] proposed extracting global Wavelet and cross line features to represent text. A forward search algorithm is applied to select features and an SVM classifier is trained to identify true text from the candidates. In [21], features of intensity mean and variance of stroke width and bounding box aspect ratio are extracted to represent CCs. Such features from the CCs are fed to a k-means algorithm for classification.

Koo and Kim [26] proposed splitting each component into eight square sub-regions, from which the following features are extracted and classified with a multilayer perceptron classifier: 1) the number of foreground pixels, 2) the number of vertical white-black transitions, and 3) the number of horizontal black-white transitions. They use the average of the classification responses from all sub-regions for text/nontext classification.

Before detected text regions are recognized by an OCR module, certain approaches use binarization, text line segmentation and character segmentation algorithms to obtain the precisely bounded characters. Segmentation has been identified as one of the most challenging problems [29], and recent approaches often integrate the segmentation step with the recognition step, or use word matching to avoid the segmentation problem.

Text binarization operates to extract text pixels and remove the background pixels. Adaptive thresholding approaches segment text according to their respective local features, and thus are adaptive to backgrounds [14]. Nevertheless, it is difficult to select a reliable threshold value for degraded text where the pixels at the text boundary often blend with the background. In this case, Gaussian mixture models could be applied given the context that a significant amount of foreground pixels are sampled to build the models [28].

The function of text line segmentation is to convert a region of multiple text lines into multiple sub-regions of single text lines. For horizontal text, the projection profile analysis of text components, presents a simple but effective method [15]. For skewed or perspective distorted text, however, the projection profile analysis method is useless before estimating the text orientation.

A recent advance of text line segmentation comes with the emergence of the skeleton analysis method [18]. Text skeletons are extracted from connected components, and a text line is defined as a continuous path on the skeleton from an intersection point to either an end point or an intersection point. The"path" corresponding to a text line does not include any other points in the middle. Given these definitions, a text region is segmented to text lines using a skeleton-cut algorithm.

Character Segmentation separates a text region into multiple regions of single characters. Vertical projection profile analysis was an early method for character segmentation. However, it is often difficult to determine an optimal projection threshold when degradation or touching characters exist.

Phan et al. [17] investigated the gradient vector flow features and a minimum cost path optimization method for character segmentation. A two-pass path search algorithm is applied where the forward search localizes potential cuts and the backward direction removes the false cuts, i.e., those that pass through the characters.

Text recognition converts image regions into strings. In recent research, word recognition has been central to text recognition because words are well-formulated with statistical models in terms of low-level features and high-level language priors. This is consistent with psycholinguistic research, where words have been the elementary units when studying human visual cognition [10]. It would seem that recognizing text at higher levels, such as clauses or sentences, has seldom been investigated because they are less tractable than words. It was demonstrated that recognizing degraded text at the character level is difficult due to the lack of language priors.

To recognize characters of a single font, general features, such as Gabor features, and simple classifiers, such as linear discriminant analysis (LDA), are often used [6].

Sheshadri and Divala [22] applied an exemplar SVM to recognize distorted characters in scene images, which makes individual decisions for each classifier and relies on decision calibration to reach a systemic consensus. Two decision calibrations for SVM scores and affine transformation estimation are used to process different distortions. Their approach achieves state-of-the-art performance in the Chars74k dataset.

V. DATASET

Table 1, [41] gives the list of commonly used datasets and summary of their features including the text categories, sources, orientations, languages, and information of training/ test samples. Selected sample images are shown in Fig. 2.

The MSRA-I, Tan, ICDAR'11 and ICDAR'13 datasets include graphic text in video, web images and email.

The ICDAR'03/054 and ICDAR'11/135 datasets are pre-pared for scene text, covering tasks of text localization, char-acter segmentation and word recognition.

The Chars74k dataset works for character recognition in natural scene images. The VIDI data set was created by Weinman et al. from images of text on signs from around a city [100]. It consists of 95 grayscale sign images with ground truth labels and ground truth character bounding boxes. There are a total of 215 words in the test set, and a training set of synthetic char-acter images from different fonts. The IIIT5K Word dataset provides cropped words (localized text) and is used inde-pendently to evaluate character segmentation and/or recog-nition approaches.

The OSTD, Tan and MSRA-II datasets that include multi-oriented text, and the NEOCR and KIST datasets that include incidental text, combine challenges from cluttered backgrounds and perspective distortions. The MSRA-II, Tan and Pan datasets that contain English and Chinese, the KAIST dataset that contains English and Korean, and the NEOCR dataset that contains eight European languages provide multilingual evaluation environments.

ICDAR'13 dataset includes 28 video sequences prepared to evaluate video scene text detection, tracking and recogni-tion. The video sequences were collected in different coun-tries including Spain, France and the United Kingdom, and were captured using a variety of hardware including mobile phones, hand-held cameras and head-mounted cameras. Recognizing text in such video sequences corresponds to certain tasks like searching for a shop in the street or finding their way inside a building.

Table 1. Commonly Used Datasets [41]

Dataset (Year)	Source	Image number (training/test)	Text number (training/test)	Orientation	Language
ICDAR'03 (2003)	Scene Camera	509 (258/251)	2,276 (1,110/1,156)	Horizontal	English
MSRA-I (2004)	Graphic & Scene Video Frames	45	158	Horizontal	English, Spanish, Chinese
Char74k (2009)	Character Camera	74,107	74,107	Horizontal	English, Kannada
VIDI (2009)	Cropped Scene Text Camera	95	215 (synthetic training images)	Horizontal	English, Kannada
KIST (2010)	Scene Camera, Mobile phones	3,000	>5,000	Distortion	English, Korean
SVT (2010)	Scene Video frames	350 (100/250)	904 (257/647)	Horizontal	English
Tan (2011)	Graphic Scene Video Frames	520	220	Multi- oriented	English, Chinese
Pan (2010)	Camera	487 (248/239)		\Multi- oriented	English, Chinese
NEOCR (2011)	Camera	659	5,238	Multi- oriented	Eight Languages
OSTD (2011)	Camera	89	218	Multi- oriented	English
ICDAR'11(2011)	Scene Camera	484 (229/255)	2,037(848/1,189)	Horizontal	English
	Graphics Camera	522(420/102)	4501(3583/918)	Distortion	English
IIIT5K Word	Web & camera	5,000 images cropped	5,000(2,000/3,000)	Distortion	English
MSRA-II(2012)	Camera	500 (300/200)	1,719	Multi-oriented	English, Chinese
ICDAR'13(2013)	Camera	462 (229/233)	848/1,095	Horizontal	English
	Web	551 (410/141)	4,501(3,564/1,439)	Multi-oriented	English
	Camera	28 videos (13/15)		Multi- oriented	Spanish, French,English
ICDAR'15(2015)	Camera	1670	1186	Horizontal	English
ICDAR'17(2017)	Camera	1555	(1255/300)	Horizontal, Multi-oriented, Curved	English

Figure 2. Sample images of text from the ICDAR'11, MSRA-I, MSRA-II, SVT, and NECOR datasets[41]

VI. CONLCUSION

This paper has described the problems related to automatic text detection and recognition in images. It has analysed the recent approaches, classification, methodologies and the various datasets available for analysis purpose. However the problems still to be addressed are end to end recognition, open vocabulary recognition, processing incidental text, processing multilingual text.

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Authors Profile

Ms. Sheetal Garg pursed Bachelor of Engineering From Amravati University and Masters of Engineering from Pune University. She is currently pursuing Ph.D. frim Vishvaraya University and currently working as Assistant Professor in Department of Computer Science and Engineering, MVJ College of Engineering Bangalore. She has published papers in International Conferences and IEEE. Her main research work focuses on Data Mining and Image Processing. She has 5 years of teaching experience.

Ms.Akshatha P S pursued Bachelor of Engineering from Visvesvaraya Technological University, and M.Tech from Lingaya's University, Haryana. She is currently working as Assistant Professor in the department of Computer Science and Engineering, MVJ College of Engineering, Bangalore. She has published and presented papers in various International Journals and Conferences. Her research interest is on Networking, Genetic Algorithms and Security. She has 9 years of teaching experience.

Ms.Kavyashree C pursued Bachelor of Engineering and M.Tech from Visvesvaraya Technological University. She is currently working as Assistant Professor in the department of Computer Science and Engineering, MVJ College of Engineering, Bangalore. She has published and presented papers in various International Journals and Conferences. Her research interest is on Networking,Artificial Intelligence and Security. She has 9.5 years of teaching experience.