DETECTION OF MULTI-ORIENTED MOVING TEXT IN VIDEOS

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ABSTRACT

Text, as one of the most significant creations of humankind, has played a vital part in humanoid life, so far from olden periods. High level semantics embodied in the text are beneficial in a wide range of vision-based applications. For example, image understanding, image indexing, geo location, automatic navigation, license plate recognition, assisting blind person and other surveillance applications. There are approaches in the field of content based image retrieval to solve the above mentioned problems. However, these approaches are inadequate to generate annotation based on semantics according to content of video or images due to opening between high level and low level features. Therefore text detection and recognition in videos grow into active and important research areas in computer vision and document analysis, which is capable of understanding the content of video and images at high level with the help of Optical Character Recognizer (OCR). Especially in recent years, the researchers has seen a flow of research efforts and considerable developments in these fields, however many challenges e.g. low resolution, complex background and variations in colors, font, font size, Multi-orientations, Multi-orientation text movements, noise, blur, and distortion still remain. The objectives of this work are in four folds: (1) to introduce a new descriptor called Histogram Oriented Moments (HOM) for detecting multi-oriented text from videos. The HOM is created by considering the orientations calculated with the second order geometrical moments. Further, to verify the detected text, optical flow properties are used to estimate the motion between text candidates in temporal frames. However, the use of temporal information is limited to false positive elimination but not as main features to find text candidates. (2) to propose new models for finding multi-oriented moving text from video and scene images through moments, motion vectors are utilized to identify moving regions that have constant velocity. However, the model is slightly sensitive to window size used for moment's calculation

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and different scripts in video. (3) To develop automatic window size determination for detecting text from videos, the next method explored stroke width transform based on the information that the stroke width remains constant throughout the characters. Further, the temporal frames are used for identifying text candidates based on the fact that caption text stays at the same unchanged location for few frames. However, the performance of the proposed method degrades when there is blur present in the video frames because moments and stroke width transforms are sensitive to blur. (4) To develop a method for text detection and recognition in blur frames, a blind deconvolution model is introduced that enhances the edge sharpness by suppressing blurred pixels. In summary, each work has been tested over benchmark datasets and authors' created datasets from different resources using standard measures. Furthermore, the results of the proposed methods are compared with the state of art methods to show that the proposed methods are competent to existing methods.

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ABSTRAK

Teks, sebagai salah satu ciptaan yang paling unggul daripada manusia, telah memainkan peranan yang penting dalam kehidupan harian, sejak zaman dulu. Semantik bertahap tinggi yang terkandung dalam teks dapat digunakan dalam pelbagai aplikasi berasaskan penglihatan. Sebagai contoh, pengertian imej, pengindeksan imej, lokasi geo, navigasi automatik, pengecaman tempat letak lesen, pertolongan kepada orang buta dan aplikasi-aplikasi pengawasan lain. Terdapat pelbagai kaedah yang berkenaan dengan pengembalian imej berasaskan kandung (CBIR) untuk menyelesaikan masalah-masalah tersebut. Walau bagaimanapun, kaedah sebegini adalah tidak mencukupi untuk menjana nota penjelasan yang berasaskan semantik yang mengikut kandungan video atau imej. Ini adalah kerana terdapat jurang besar antara ciri-ciri tahap rendah dan tinggi. Oleh itu pengesanan dan pengecaman teks dalam video telah berkembang ke bidang-bidang visi computer dan analisa dokumen yang penting dan aktif, iaitu pemahaman kandungan video dan imej pada tahap yang tinggi dengan bantuan Pengecam Aksara Optik (OCR). Pada tahun-tahun kebelakangan ini, para penyelidik telah menyaksikan usaha-usaha penyelidikan dan perkembangan yang besar dalam bidang ini, namun pelbagai cabaran seperti resolusi rendah, latar belakang yang kompleks dan penukaran warna, perkataan, saiz perkataan, orientasi majmuk, pergerakan teks dalam orientasi majmuk, hingar, kabur, dan herotan, masih kekal. Terdapat empat objektif dalam kajian ini: (1) untuk memperkenalkan penghurai baru yang dikenali sebagai momen berasaskan histogram (HOM) untuk mengesan teks berorientasikan majmuk dari video. HOM direka cipta dengan mengambil kira orientasi yang dikira dengan momen geometri peringkat kedua. Selanjutnya, untuk mengesahkan teks yang dikesan, ciri-ciri aliran optik, telah digunakan untuk menganggarkan pergerakkan antara bingkai tempoh. Walau bagaimanapun, penggunaan maklumat tempoh adalah terhad kepada penghapusan positif palsu tetapi bukan sebagai ciri-ciri

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utama untuk mencari teks-teks calon. (2) untuk mencadangkan model baru yang dapat mencari pergerakkan teks yang berorientas majmuk daripada video dan imej pemandangan, dengan menggunakan momen. Vektor gerakan digunakkan untuk mengenal pasti kawasan-kawasan yang mempunyai halaju tetap. Walau bagaimanapun, model ini didapati sensitif kepada saiz tetingkap yang digunakan untuk pengiraan momen dan skrip yang berbeza dalam video. (3) Untuk menentu saiz tetingkap secara automatik bagi pengesanan teks dari video. Jelmaan strok lebar diterokai di mana strok lebar adalah tetap sepanjang masa. Selanjutnya, bingkai tempoh juga digunakan untuk mengenal pasti teks-teks calon dengan berdasarkan fakta bahawa teks kapsyen kekal di lokasi yang tetap untuk beberapa bingkai. Walau bagaimanapun, kaedah ini tidak dapat dijalankan dengan baik untuk video yang kabur. Ini adalah kerana momen dan jelmaan strok lebar adalah sensitif kepada kabur. (4) Untuk mengusahakan suatu kaedah yang dapat mengesan dan mengecam teks dalam bingkai kabur. Model nyah-konvolusi buta telah diperkenalkan untuk meningkatkan amatan tepian dengan menyekat piksel yang kabur. Rumusannya, setiap kerja telah diuji ke atas set data yang sedia ada dan set data yang dikumpulkan daripada pelbagai sumber dengan langkah-langkah piawai. Tambahan lagi, keputusan kaedah yang dicadangkan adalah dibandingkan dengan kaedah-kaedah lain untuk menunjukkan bahawa kaedah yang dicadangkan adalah lebih baik berbanding dengan kaedah yang sedia ada.

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ABBREVIATIONS

APT:	Average Processing Time
ATA:	Average Tracking Accuracy
ATB:	Actual Text Blocks
BDM:	Block Distortion Measure
BRISQUE:	Blind/Reference less Image Spatial Quality Evaluator
CBIR:	Content Based Image Retrieval
CC:	Connected Component
CRF:	Conditional Random Field
F:	F-measure
FDB:	Falsely Detected Block
GD:	Gradient Direction
GPC:	Global Phase Coherence
GVF:	Gradient Vector Flow
GW-L1:	Gaussian Weighted-L1 norm
HOG:	Histogram Oriented Gradients
HOM:	Histogram Oriented Moments
KNFB:	Kurzweil National Federation of the Blind
MDB:	Text Block with Missing Data
MDR:	Misdetection Rate
MOTA:	Multiple Object Tracking Accuracy
MOTP:	Multiple Object Tracking Precision
MSER:	Maximally Stable Extremal Region
NRIQA:	blind/No-Reference (NR) Image Quality Assessment (IQA)
OCR:	Optical Character Recognizer

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P:	Precision
QA:	Quality Assessment
R:	Recall
SI:	Sharpness Index
SW:	Stroke Width
SWT:	Stroke Width Transform
TDB:	Truly Detected Block
TV:	Total Variation
WHO:	World Health Organization

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CHAPTER 1: INTRODUCTION

1.1 Overview

In the abundance of online information present in the form of text videos, with the evolution of mobile devices and the entry of new concept like augmented reality, text detection is trending in recent years. The emergence of applications on mobile devices that translate text into other languages in real time has stimulated renewed interest in the problems. One of the most expressive means of communications is text which can be embedded into documents or into scenes or into a video as a means of communicating information. This is done in the way that makes it noticeable and/or readable by others. The collection of massive amounts of street view data is just one driving application. Other well-known examples are vehicle license, signs containing text from a natural scene detection and recognition. Text in web images is relevant to the content of the web pages. Video captions annotate information about the happening events. Expansion of mobile devices containing digital cameras has made imaging devices widely available. Embedded module assists mobile devices to automatically input name cards, white boards and slide presentations. Without being forced to input by keyboard, users feel more comfortable and work more efficiently. Traffic Signs in natural scenes carry significant information. Traffic sign recognition and translation systems aid users to overcome language barriers (Chen, Odobez, & Bourlard, 2004; J. Zhang & Kasturi, 2008).

In general, text recognition in video consists of four steps: (1) Pre-processing of input image or video frame that includes the removal of blur, noise or other distortion present in video. (2) Text detection, finding region in image or video frame that contains text which results in text with closed bounding box. In other words, it requires separating text from non-text regions in video. (3) Text binarization is separating foreground (text pixels) from background (non-text pixels) information in the images

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by representing text pixels as white pixels and non-text pixels as black pixels. (4) Text recognition which uses Optical Character Recognizer (OCR) engine for recognition. Recently (Harris & Stephens, 1988; Neumann & Matas, 2015), methods are proposed that do not use binarization step in order to avoid loss of information during binarization for text detection and recognition in video and natural scene images. However, these methods extract large number of features using gray information and use classifier for detection and recognition. Since these methods depend on classifier and large number of training samples, the methods limit their ability to detect and recognize the particular script. Furthermore, developing separate OCR for video images is not necessary when OCR of plain document images is available in publicly. Therefore, the thesis uses binarization to validate the results of text detection methods as the main aim of the thesis is text detection in video images not recognition.

Among these steps, text detection and binarization are essential, challenging and have attracted much research attention because the success of recognition system depends on these steps. The logical flow of the recognition system can be seen in Figure 1.1. The thesis focuses on preprocessing that deblur the video images with new algorithm because blur is quite common in case of video images. Then text detection in video images as it is challenging and the success of recognition depends on success of text detection step.

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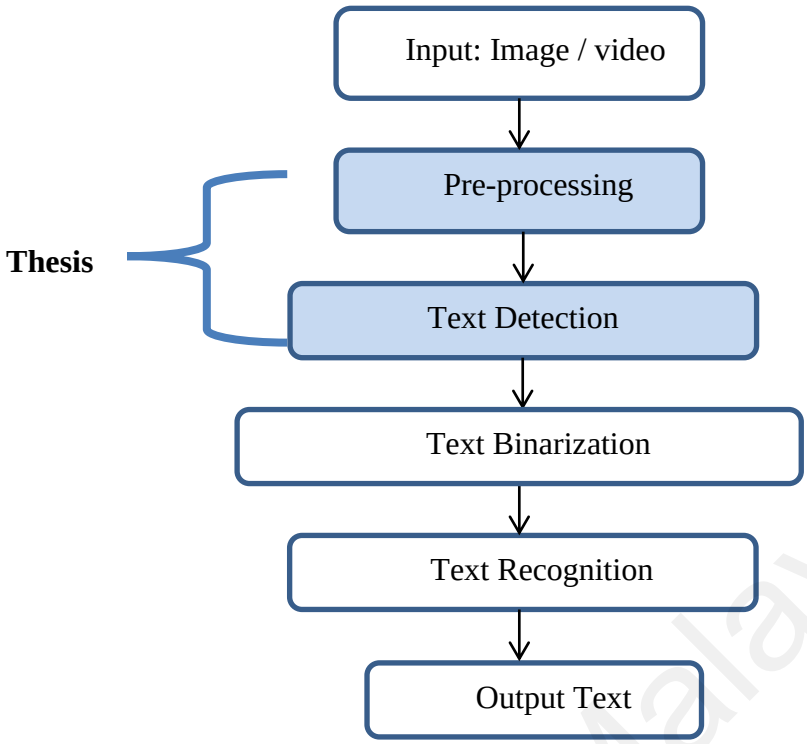

Figure 1.1: Steps of automatic text recognition system

Text detection and recognition is an old problem for document analysis where researchers developed many successful methods. One such successful application is Optical Character Recognizer (OCR) engine (Tesseract). However, this OCR engine has its own inherent limitations, such as binary image, size of the character image, shape to be preserved, high contrast image, plain background image etc. As a result, these approaches may not be appropriate for images like video where one can expect large variations in contrast, background and foreground. It can be confirmed from sample images shown in Figure 1.2 (a)-(d) where Figure 1.2 (a) is a scanned document image which contains plain background and Figure 1.2 (b)-(d) are natural scene and video images which contains complex background and variations in text. To overcome the problem of complex background images such as text detection in natural scene images which generally captured by high resolution camera as shown in Figure 1.2 (b), several methods are developed (Qiaoyang Ye & Doermann, 2014; Qixiang Ye & Doermann, 2015). Since images captured by high resolution camera, images contains

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high contrast text information. Hence, the methods developed for detecting text in natural scene images work well for high contrast images but the performance of the method degrades for low contrast text image like video where one can expect both low and high contrast images as shown in Figure 1.2(c). It is true that there are devices to capture high resolution videos in today's world. However, since storing video requires huge memory, the trend is to capture low resolution video to save memory. Therefore, video image may contain both high contrast and low contrast. The main problem with low contrast images is that it may cause more disconnections and loss of information compared to high contrast images where complete shape without much disconnections and loss of information is expected. Besides, usually video comprises two kinds of text: Caption/superimpose/artificial text which is manually edited text and Scene text which is naturally existing text as in natural scene images. Since caption text is edited text, it has horizontal direction, good quality, clarity, and contrast while scene text exists naturally; it is unpredictable as shown in Figure 1.2 (d). As a result, due to the presence of two different types text in video, the complexity of the problem increases in contrast to text detection in natural scene images. Hence, text detection in video requires special attention of researchers to tackle the issues with video text detection system.

The occurrence of both graphics and scene texts in video increases the complexity of the problem. Text information born in digital images is considered to be an essential aspect of overall image understanding. At the same time, text information extractions from videos and natural scene images have many challenging issues. The challenges lie in numerous issues, such as alignment of text, variation of the light intensity, font size, color, and camera angles (Qiaoyang Ye & Doermann, 2014). Challenges in detail will be discussed in subsequent section. Examples of video images with text information can be found in Figure 1.2 (c) and (d).

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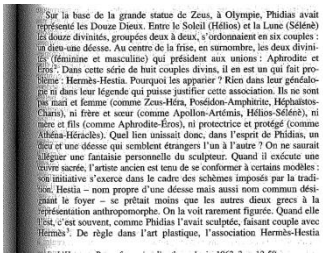

(a) Text in document images

(b) Text in Natural Scene images

(c) Graphics Text in Video

(d) Scene text in Video

Figure 1.2: Example of text information present at different sources

Document analysis methods help in detecting text from plain document images, such as print text image, handwritten text images etc. Similar to that the methods that work for natural scene images are good for understanding scenes, such as sign board, bill board, building names, street names etc. In the same way, due to invention of new digital devices and technology; storing, capturing, and processing large data has become easier. For example, cloud computing concept for storage, parallel processing for performing operations, advanced internet and network for communication and transportation etc. As a result, people prefer to capture video rather than images to grab more information and details. The text based retrieval system helps in retrieving video accurately and efficiently according to semantic of video as the meaning of text is close to content of the video. Therefore, the existing methods that developed for scanned images and natural images may not be suitable for handling videos of the above mentioned applications.

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For example, caption text in video can be used for event identification, news reader identification and news channel understanding while scene text in video can be used for tracking and surveillance applications. This research is greatly motivated by the vast range of real time applications to find more robust solutions for detecting text from scene images and videos. For instance, according to the World Health Organization(WHO), approximately 286 million visually impaired and 38 million legally blind people living in the world. Creating personal text-to-speech devices assists them in understanding road sign boards, product and pharmaceutical labels, grocery signs, and currency and ATM instructions (Ezaki, Kiyota, Minh, Bulacu, & Schomaker, 2005; Xu Liu, 2008). The University of Maryland (Xu Liu, 2008) and City University of New York (Yi & Tian, 2012) have developed text recognition prototypes for visually impaired people. The Kurzweil National Federation of the Blind (KNFB) reader2 runs on mobile application, which allows reading text from indoor scenes to people who are visually impaired.

Similarly, in the last few years, advancement of new technologies in the field of information retrieval has been changing in day to day life of humans (Jung, Kim, & Jain, 2004; Sharma, Shivakumara, Pal, Blumenstein, & Tan, 2012). It is evident from the official statistics of the popular video portal, YouTube that almost 60 hours of videos are uploaded every minute and more than 3 billion videos are watched per day over YouTube. Therefore, retrieval of the videos on World Wide Web (WWW) has become a very important and challenging task for researchers (X. Wang, Song, Zhang, & Xin, 2015).

The complication of applications, environments, flexible image capturing styles and variations in text contents poses various challenges, which are categorized in Table 1.1 as follows,

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Table 1.1: Challenges in Text Detection

Category	Subcategory
Text content	Variation of font size Multi-oriented (or) curved text Variation of font style Multilingual Text Graphics Text Scene Text
Image capturing	Blurring (or) degradation Perspective distortion
Environment effect	Scene complexity (Complex background) Illumination effects

Font Size: since video images contains scene text, variations in font and font size if common as it depends on object embedded in background while caption text in video image has uniform font and font size at least for that image. It can be seen in Figure 1.3 (a) & (b) where texts of different font type and font size are present.

Multi-oriented (or) curved text: Extracting feature which are invariant to rotation is hard and it is essential for scene text detection in video. Traversing cured text to fix closed bounding box around is a real challenge. In addition, single frame may contain different oriented scene text and horizontal caption text. This adds more complexity to the problem as shown in Figure 1.3 (b).

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(a) (b) (c)

(d) (e) (f)

Figure 1.3: Challenges in detecting text

Multilingual environments: Most of the existing methods developed are targeting English text but the same methods may not good for multi-lingual text as in Figure 1.3 (b) because the shape of characters varies from one script to another script. Since text detection is pre-processing step for recognition, the developing method should work for the text of any scripts. Extracting features which are invariant script for text detection in video is another challenge.

Blurring and degradation: Due to camera movements or object movements or defocusing, there are high chances introducing blur, perspective distortion, loss of information, contrast variation etc. as in Figure 1.3 (c). Therefore, a robust text detection method should be able to withstand the aforementioned challenges.

Low resolution: In general, cameras used for capturing video have low resolution to store more videos as mentioned in the above compared to the camera which capture individual images. This results in low quality images which lead to more

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disconnections, loss of information, loss of shapes, loss of structure etc. Extracting features which detect text of low contrast pixels from high contrast background pixel is challenging.

Scene complexity (Complex background): In natural locations, several man-made objects, such as houses, symbols and paintings appear, that can have similar looks and structures as text, as shown in Figure 1.2 (d) & (e). It is hard to predict the background changes and variations. Surrounding scene makes it difficult to discriminate text from non-text in complex scene environment.

Illumination effects: When capturing images or recording video in the open environment, irregular lighting is common due to the illumination and the uneven response of sensory devices, as shown in Figure 1.2 (f). Uneven lighting creates corrosion of visual features and color distortion, and therefore introduces false detection, and recognition results.

The work presented in this thesis is greatly motivated by the huge number of applications and challenges involved in text detection from videos. The scope of this thesis is limited to develop methods for text detection in video because it is complex step compared to other intermediate steps of text recognition system. In addition, only few methods target text detection from videos.

1.2 Objectives

The main objectives of this thesis are as follows,

i. To introduce a new descriptor for text detection in video which is invariant to rotation, scaling, font, and font size variations.

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ii. The motion vectors and optical flow properties are utilized for identifying moving text from videos. In addition to that text motion properties are used to verify the text region.

iii. To detect blur text in video images a new deblurring method is proposed. This model improves text detection accuracy in blur environment.

iv. Proposed methods are designed, implemented and validated using publically acceptable standard database.

v. To evaluate the usefulness and effectiveness of the proposed approaches, it has been compared with the latest and well known existing methods.

1.3 Contributions

The contributions of this thesis to detect text from videos are as follows:

1. The first contribution of this thesis is to develop a new descriptor called Histogram Oriented Moments (HOM). Inspired by the well-known descriptor called Histogram Oriented Gradients (HOG) used for object recognition, classification in computer vision field, the proposed method proposes a new descriptor called Histogram Oriented Moments (HOM) that explores moments for determining orientations unlike HOG uses gradient (Minetto, Thome, Cord, Leite, & Stolfi, 2013). From experimental analysis it has been noticed that HOM is more effective when compared to HOG because HOG detects more non-text components compared to HOM. HOM is invariant to rotation, scaling, font, and font size variations. The proposed descriptor is able to detect both static text and dynamic text from video frame, and then utilize the optical flow that is temporal information to detect the moving text. In this contribution, temporal information is used only at text blocks level for removing false positives but not as a main feature for text detection.

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2. The second contribution of this thesis proposed a method to detect moving text. The method utilizes temporal information. The proposed method utilizes motion vectors for identification of moving blocks that have same velocity. For every block, moments are calculated and k-means clustering algorithm is applied to identify text blocks. Then gradient direction (Epshtein et al., 2010) of character candidates are investigated and observed. This results in the special characteristic that is the many of the gradient direction of outer contour pixels of character components moves towards the character centroid and few moves away from the character. This observation inspires us to propose a rule for finding potential text candidates from the text candidate s. Then region growing method is used to extract multi-oriented text line, which uses nearest neighbor criterion for finding neighbor components along text line direction as proposed in (Palaiahnakote Shivakumara, Dutta, Tan, & Pal, 2014) for text detection in individual frames. Since the method uses fixed window size for moment calculation, it is sensitive to text lines of different scripts in video.
3. The third contribution of the thesis examines geometric moments for identifying moving as well as non-moving text of any orientation and script in video. The method produces higher accuracy than the method proposed in second contribution. The deviation for the moments between first frames and successive temporal frames is estimated to identify the text components and background components with the help of k-means clustering algorithm. In addition, the stroke width transform is proposed to determine the automatic window size. Furthermore, to extract full text lines of arbitrarily-oriented texts, boundary growing is proposed. For which the nearest neighbor growing in gradient direction is proposed. This method does not consider blurred frames for text

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detection as the stroke width based features are sensitive to blur information in video.

4. Finally, in fourth contribution a new deblurring method is proposed to detect the blur text present in videos. It is evident from the paper (Kim, Jung, & Kim, 2003) that blur is the main cause to get poor accuracy of the methods because edge or gradient-based methods are sensitive to blur and distortions. These issues can be resolved in two ways: (1) developing a method which can withstand causes given by blur artifact and (2) developing a method for deblurring the blur image to restore the structure of the components. The proposed work select the second approach because developing a method which is invariant to blur is challenging (C. Liu et al., 2005). In using the proposed deblurring model the text detection and recognition accuracy improved.

In summary, the collective impact of the four contributions will constitute to an efficient and robust text detection method in video images. In addition, the proposed work is able to detect both static text as well as moving text without affecting the above mentioned causes.

1.4 Organization of Thesis

This thesis is organized into seven main chapters as described in the followings:

Chapter 2 reviews the state-of-the-art solutions, methods and strategies which are relevant to the video text detection.

Chapter 3 presents description on the proposed descriptor called Histogram Oriented Moments (HOM) for text detection in video. The proposed method uses optical flow properties to detect moving text. To validate the proposed method over

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existing methods, experimentation is performed on ICDAR 2013 video dataset and author's video dataset.

Chapter 4 presents detailed explanation on the proposed method that uses motion vectors with moments to detect moving text. The proposed technique is tested on both static and moving text videos to evaluate the performance. The results are compared with the well-known existing methods to show effectiveness of the proposed method.

Chapter 5 provides details of the proposed method that is capable of detecting text line of any orientation in multi-script environment. The method is able to automatically determine the number of frames and window size to be used for text detection process. Experimental results are represented on standard video, namely, ICDAR 2013, ICDAR 2015, YVT videos and authors own English and Multi-lingual video to demonstrate that the proposed method outperforms the existing methods.

Chapter 6 provides detailed description of the proposed deblurring model to deblur the video images containing text to improve the text detection accuracy. The proposed deblurring model is compared with other existing models to demonstrate its superiority. In addition, to validate the usefulness and the effectiveness of the proposed model, text detection and recognition experiments are conducted on blurred images of video databases, namely, ICDAR 2013, ICDAR 2015, YVT and then standard natural scene image databases, namely, ICDAR 2013, SVT, and MSER. Text detection and recognition results on both blurred and deblurred video/images illustrate that the proposed model improves the performance significantly.

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Chapter 7 concludes the thesis with some recommendation for the future work.

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CHAPTER 2: LITERATURE REVIEW

In this chapter, various well-known conventional text detection methods in video domain will be reviewed. Particularly, the review includes the recent advances in text detection approaches followed with the survey on deblurring techniques for restoring the text images/frames.

2.1 Text Detection from Videos

A large number of approaches have been proposed in the literature for detecting text in video. These can be classified into two broad categories (Y.-K. Wang & Chen, 2006; Wu, Shivakumara, Lu, & Tan, 2015; J. Xu, Shivakumara, Lu, Tan, & Uchida, 2016), (1) the methods which do not use temporal information and (2) the methods which use temporal information. The methods fall on category-1 generally use first frame or key frame of video for text detection. These methods either assume key frames containing text is available or use existing methods for extracting key frames. The methods that fall under category-2 prefer to use temporal information for enhancing text of low resolution or reducing false positives but not for tracking text or for the detection of moving text. Generally, these approaches combine several frames into single enhanced frame to produce small details of texts and for eliminating false positives. The big query lies in determining the exact number of frames for the enhancement process.

2.1.1 Methods without Temporal Information

Methods that do not utilize temporal information can further be classified into three classes, namely, connected component (CC) based methods, texture based and edge/gradient based methods (J. Zhang & Kasturi, 2014).

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2.1.1.1 Connected Component based methods

Bottom-up approach has been used by connected component based methods by merging small components into successively larger components till all regions are covered in the image (Weilin Huang, Lin, Yang, & Wang, 2013; JIANG et al., 2006; Z. Liu & Sarkar, 2008; Lu & Tan, 2006). A geometrical analysis is frequently desired in later phases to find text components and assemble them to localize text regions. CC-based methods straightaway classify candidate text components by color clustering or edge detection. The non-text components are then removed with heuristic rules or classifiers. Since the amount of segmented candidate components is comparatively small, CC-based methods consumes less processing time and found text components can be directly used for recognition. However, CC-based methods cannot detect text correctly without prior knowledge of text scale and position. Moreover, designing reliable and fast connected component analyzers is hard since there are many non-text components which are easily confused with texts when analyzed individually. Also, CC-based methods exploit characteristics of text components for text detection in video because text components properties help us to separate background from the text information. For example, several methods are discussed in the survey by Jung et al. (Jung et al., 2004).

In the paper proposed by Zhang et al. (H. Zhang, Liu, Yang, Ding, & Wang, 2011), 'text' or 'non-text' labeled by conditional random field to give connected components. This paper is extended work from the algorithm proposed in (Y.-F. Pan, Hou, & Liu, 2011) that also uses a Conditional Random Field (CRF) model. And backgrounds that possess same characteristics as text are recognized as text characters with a low confidence. Then the authors in this paper proposed a two-step iterative CRF algorithm with a Belief Propagation inference stage and an OCR filtering step. Two types of neighborhood association graph are utilized in the respective iterations for extracting

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multiple text lines. The first CRF iteration targets at finding certain text components, especially in multiple text lines, and sending uncertain components to the second iteration. The second iteration gives second chance for the uncertain components and filter false alarm components with the assistance of OCR. The proposed method aims at extracting text lines, instead of separated words as the ground truth of ICDAR2005 competition, which contributes to a reduction of precision and recall rate.

Neumann et al. (Sun, Huo, Jia, & Chen, 2015) proposed character stroke area estimation for detecting text. The proposed feature is invariant to scaling and rotation. The initial hypothesis is drawn from MSER. Followed by, determining the stroke area ratio, aspect ratio, compactness, convex hull area ratio and holes area ratio to define the text regions. The methods require more text information like text line for achieving good results. However, video images sometimes contain words with few characters and it is common that limits the performance of this method.

Wang et al. (Kongqiao Wang & Kangas, 2003) proposed a connected component based method to find characters in scene images. The method also distinct color images into homogeneous color layers. Then each connected component is analyzed in color layers using block adjacency graph similarity. For characters detection, an aligning and analysis scheme is introduced by author to locate all the potential characters candidates in all color layers. Huang et al. (Weilin Huang et al., 2013) presented a Stroke Feature Transform, new operator based on Stroke Width Transform. In direction to resolve the disparity problem of edge points in original Stroke Width Transform, SFT proposed color consistency and constrains relations of local edge points, resulting better component extraction results. Although the method works well in comparison with existing method but it is limited to horizontal texts.

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Wang and Kangas (H. Wang & Kangas, 2001) introduced a method based on basic localization on connected component analysis. CC's are extracted from each decomposed layer (weak color space, gray-scale space, and hue space). Block candidates are checked by alignment analysis. Character segmentation by (Priority adaptive segmentation) algorithm extracts characters in the final composed image. This algorithm is not so robust to multi-scale size, variant illumination, over lighting and low contrast.

Neumann and Matas (Jacob & Thomas, 2015) detected character components as Extremal Regions (ER) which is selected in a two stage classification. First, operating on a coarse Gaussian scale space pyramid and second, on multiple image projections. The performance of the method degrades because ER is sensitive to disconnections.

Wang and Kangas (H. Wang, 2001) described a CC-based method for automatic text detection and segmentation from natural scene images. To deal with the complexity of color background, a multi-group decomposition system is used. CC extraction is implemented by means of block adjacency graph algorithm after noise removal and run length smearing operation. Some heuristic features and priority adaptive segmentation of characters are proposed in block candidate verification and gray-scale-based recognition.

Chen et al. (Chen & Odobez, 2005) proposed a sequential Monte Carlo based method for text detection in video. This method uses Otsu thresholds to segment initial text regions and then it uses distribution of pixels of each segmented region for classification of text pixels from the background. (Y. Liu, Song, Zhang, & Meng, 2013) proposed a method for multi-oriented Chinese text extraction in video. This method utilizes the combination of wavelet and color domains to obtain text candidates for the

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given video image. For every text candidate, the method extracts features at component level for classifying component as text or non-text.

In summary, it is observed from the discussion on connected component based methods that these methods focus on caption or superimposed text but not scene text because caption text has better quality and contrast compared to its background. Therefore, these methods expect the shape to be preserved as in document analysis and use uniform color features and shape features. These methods are sensitive to complex background because components in background may produce text like features. In addition, these methods are limited to high contrast text but not to scene texts which can have variation in contrasts. To overcome the problems associated with connected component based methods, texture based methods have been proposed for text detection in video which considers appearance of a text pattern as a special texture.

2.1.1.2 Texture based methods

To alleviate the problems of connected based methods, texture-based methods are proposed. These methods consider appearance of text as special texture property for detecting text in video. These methods use texture analysis techniques such as Wavelet decomposition, Gaussian filtering, Discrete Cosine Transform, Local Binary Pattern, and Fourier transform. Usually, features are extracted over a certain region and a classifier (trained using machine learning techniques or by heuristics) is applied to identify the existence of text because text regions have distinct textural properties from non-text ones, these methods can detect and localize texts accurately even when images are noisy. However, it has relatively slower speed and the performance of method is sensitive to text alignment orientation.

Zhou et al. (Palaiahnakote Shivakumara, Phan, & Tan, 2009) proposed a text detection method for multilingual text, which emphases on finding all the text regions

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in natural scene irrespective of their language variety. According to guidelines of writing system, three different texture features are nominated to describe the multilingual text: local binary pattern, mean of gradients and HOG. Finally, cascade Ada Boost classifier is adopted to combine the influence of different features to decide the text regions. This work is similar to the methods illustrated in paper (Hanif & Prevost, 2009; Hanif, Prevost, & Negri, 2008).

Pan et al. (Y.-F. Pan, Liu, & Hou, 2010) proposed a new method for fast text detection in natural scene images by combining learning-based region finding and verification using a coarse-to-fine strategy. Unlike methods that use learning-based classification for only filtering or verification, a boosted classifier and a polynomial classifier are used for coarse region filtering and fine verification respectively with selecting discriminative features. For the verification step, the method evaluates five widely used features: HOG, local binary pattern, discrete cosine transform, Gabor, and wavelets. A weak classifier selection based on computational complexity and boosting framework integrating feature is proposed to construct efficiently detecting text in the paper proposed by Shehzad Muhammad et al. (Hanif & Prevost, 2009). The proposed system that builds a larger set of features by combining small set of heterogeneous features. A neural network based localizer learns necessary rules for detection. Three different types of features HoG, Standard Deviation and Mean Difference Feature are extracted from a text segmentation block. Ji et al. (Ji et al., 2008) uses local Haar Binary Pattern for robust text characterization. The method especially addressed the issues of text-background contrasts and variant illumination. More specifically, threshold restricted local binary pattern is extracted from high-frequency coefficients of pyramid Haar wavelet, calculated at different resolution to signify multi-scale texture information. Local Haar Binary Pattern can preserve uniform inconsistent text-background contrasts while filtering gradual illumination variations. Presumed that

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occurrence between certain directions were notable, directional correlation analysis was used to locate candidate text regions.

Saoi et al. (Saoi, Goto, & Kobayashi, 2005) proposed a novel unsupervised clustering method for the classification of multi-channel wavelet features to deal with color images, as the proposed algorithm in required the ability of discriminating color differences. The key contributions in the paper consist of the following steps: decomposing color image into R, G, B channel images and making 2D Wavelet Transform of every decomposed image, then utilizing the unsupervised pixel block classification with the k-means algorithm in combined feature vector space and integrating results of three channels by logical OR.

Angadi and Kodabagi (Angadi & Kodabagi, 2009) introduces a novel texture based text detection method. This uses a high pass filtering in the DCT domain to remove most of the background. Then the homogeneity and contrast based feature vectors are calculated to detect text area. Though the algorithm is robust and achieves good detection rate on a variety of 100 low resolution natural scene images, this paper primarily focused on the localization of rough estimate text blocks.

Gllavata et al. (Gllavata, Ewerth, & Freisleben, 2004) proposed a method based on unsupervised classification of high frequency wavelet coefficients for accurate text detection in video frames. The method used a sliding window to move over the transformed wavelet images and characterized the areas with the distribution of high-frequency wavelet coefficients. Then classifies the predefined regions into three parts by k-means algorithm: text, simple and complex backgrounds.

Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010) proposed a method based on the combination of wavelet and color features for detecting text candidates

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with the help of k-means clustering. Boundary growing has been proposed to extract text lines of different orientations in video. Shivakumara et al. (P. Shivakumara et al., 2010) proposed a method which combines Fourier transform and color spaces for text detection in video. Though the methods work well for complex background of the video, the methods require more number of computations because of expensive transformation is involved in text detection process. However, the primary focus on these methods is on horizontal text detection in video but not arbitrarily-oriented text in video. Recently, Liang et al. (Guozhu, Shivakumara, Tong, & Chew Lim, 2015) proposed a method based on multi-spectral fusion for arbitrarily-oriented scene text detection in video images. The performance of the method degrades for the multi-script images. In addition, the method does not utilize the temporal information for text detection though it is available in video.

Wang & Chen (Y.-K. Wang & Chen, 2006) have proposed spatial-temporal wavelet transform to enhance the video frames. For the enhanced frame, this method extracts a set of statistical features by performing sliding window over an enhanced image. Then a classifier was used for classifying the text and non-text pixels. (Anthimopoulos, Gatos, & Pratikakis, 2013) proposed a method for artificial and scene text detection in images and videos using a Random forest classifier and a multi-level adaptive color edge local binary pattern. The multi-level adaptive color edge local binary pattern has been used to study the spatial distribution of color edges in multiple adaptive levels of contrasts. In continuation, gradient based algorithm has been applied to achieve text detection in video/images.

In summary, it is noted from the review of texture based methods that most of the methods use a large number of features and classifier with a large number of training samples. Therefore, these methods are said to be computationally expensive though the

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methods work well for complex background in contrast to connected component based methods. In addition, the methods scope is limited to be used with specific scripts because of constraints of classifiers and training samples. To achieve better efficiency and accuracy for the text detection in video, the methods based on edge and gradient information are developed.

2.1.1.3 Edge/Gradient Feature based methods

It is fact that characters in text are formed with the combination of horizontal, vertical and diagonal edges. Identifying the presence of such prominent edge information is the main basis for developing edge/gradient based methods. As a result, one can expect high gradient values for text information and low gradient values for non-text information due to high contrast at edges. Further, the methods explore edge and gradient information for text detection based on the fact that dense pixels with unique spatial relationship between edge where text is presents.

For example, Liu et al. (C. Liu et al., 2005) extracts a set of statistical features from the edge images of different directions. Then k-means clustering has been used for classifying text and non-text pixels. Geometrical properties have been used for grouping text pixels and to extract text line in video and images. Shivakumara et al (Palaiahnakote Shivakumara et al., 2012) proposed multi-oriented video scene text detection in video using Bayesian classifier and boundary growing. This method uses the combination of Sobel and Laplacian operation for enhancing the text information. Then the Bayesian classifier has been used for classifying text and non-text pixels based on generating three probability matrices. Similarly, the (gradient vector flow) and grouping based method are proposed by (Palaiahnakote Shivakumara, Yuan, Zhao, Lu, & Tan, 2015) for arbitrary orientation text detection in video. This method addresses the complex arbitrary orientation problem by combining GVF information and

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grouping strategies. Though it solves complex problem, it does utilize the temporal information, rather rely on individual frames of video. This limitation makes the methods to produce inconsistent results for the different data and applications.

Cho et al. (X. C. Yin, Pei, Zhang, & Hao, 2015) exploits the similarity between edges of image with text edges using canny edge detector. The proposed method does non-maximum suppression, double threshold classification, and text tracking to localize the text region. Although the method is simple and effective but it is limited to only scene text. A new pixel intensity based stroke width detector is proposed in (Hu, Wang, & Lu, 2015). The text is detected using Stroke-specific keypoints which are efficiently detected by local thresholding guided by keypoint properties.

Wei and Lin (Wei & Lin, 2012) proposed a robust video text detection method using Support Vector Machine (SVM). This approach generates two downsized images for the input image and then performs gradient difference for the three images including the input image which results in three gradient difference images. K-means clustering is applied on the difference images to separate text cluster from non-text. Finally, the SVM classifier has been used for classifying true text pixels from the text clusters. Shivakumara et al.(Palaiahnakote Shivakumara et al., 2009) derive rules using the different edge maps of the input image. The rules have been used for segmenting text region and then the same rules are modified for extracting text information from the video images. (Lienhart & Wernicke, 2002) have proposed a method based on the combination of gradient and RGB color space. This results in different directions of edge maps for the input image. Then neural network classifier is applied for separating text and non-text pixels. Further, refinement has been proposed for full text line extraction.

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Sun et al. (Qixiang Ye, Jiao, Huang, & Yu, 2007) introduced a method to extract board text under natural scene. The method is constructed upon color image filtering procedures, where rims are first obtained, followed by an analysis on relationships among characters and inherent features. The approach was presented to work efficiently on board text under natural scenes.

(Xiaoqing Liu & Samarabandu, 2006; Ou, Zhu, & Liu, 2004) proposed an edge-based multi- scale text detection algorithm, which can automatically detect and locate text in complex background images. Edge density, strength and the variance were used as the three distinguishing characteristics of text embedded in images, which can be used as main features for detection. It is strong and gives good results with respect to the orientation, font style, size, color, and orientation of text and can be used in many application fields, such as vehicle license detection and recognition, mobile robot navigation, document retrieving, page segmentation, and object identification.

(CUI, YANG, & LIANG, 2006) proposed a system that first utilized the Roberts operator to compute edges, which uses a self-adaptive threshold to process binary image, and utilizes erosion operator in mathematical morphological to eliminate nonlinear influence and outstand linear feature. Then, the method proposed focusing function based projection, finding text region required and completing text extraction.

(Ezaki, Bulacu, & Schomaker, 2004; Jain & Yu, 1998) detected text location in complex background images. The method proposed an effective edge-based algorithm for text detection in natural scene images. First it performed pyramid decomposition, then color-based edge detection and binarization is performed. Later the mathematical morphology method, the text of the color image is extracted by the restriction of text regions at last. Carried experiment on a large number of images selected from the

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ICDAR2003 database (Lucas et al., 2003), this algorithm shows its robustness and accuracy against variations in text color and font size.

Zhang and Kasturi (J. Zhang & Kasturi, 2014) proposed a text detection method based on character and link energies. The method explores stroke width distance to define link energies between the character components on the basis of stroke width distance of the character components is generally almost same. Then a maximum spanning tree is used for text line extraction from both images and videos.

In summary, it can be inferred from the literature review on edge and gradient based methods that these methods are fast compared to texture based methods, but these are sensitive to background because edge and gradient are not robust to complex background variations. This results in more false positives. Therefore, few hybrid methods also developed that usually combines the benefits of connected component based, texture based methods or edge based methods. Hybrid methods (Y.-F. Pan et al., 2011; Yangxing & IKENAGA, 2006) are a combination of texture based methods and component based methods, which make use of the advantages of these two types of methods. In the method proposed by Liu et al. (Yangxing & IKENAGA, 2006), edge pixels of all possible text regions were extracted using an elaborate edge detection strategy, and the gradient and geometrical properties of region contours are verified to generate candidate text regions, followed by a texture analysis procedure to distinguish true text regions from non-text regions.

Pan et al. (Y.-F. Pan et al., 2011) presented a hybrid method for detecting and localizing texts in natural scene images by a scale-adaptive segmentation algorithm designed for stroke candidate's extraction and a CRF model with pair-wise weight by local line fitting designed for stroke verification. This algorithm achieved competitive results in the ICDAR 2005 competition.

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Overall, in conclusion the methods that do not utilize the temporal information can be summarized as in Table 2.1.

Table 2.1: Summary of the methods that does not utilize Temporal Information

Methods	Advantages	Limitations
Connected component based methods	Good for plain background and high contrast images	Require the characteristics of character components Focused on only caption text Not robust to multi-scale size, variant illumination, over lighting and low contrast
Texture based methods	Good for complex background images	Sensitive to font type or font size and are computationally expensive Performance get affected by blur artifacts
Edge/Gradient Feature based methods	Fast and effective	Produce more false positives for complex background images Inconsistent results for the different data and applications More false detection is possible

However, despite temporal information is available for video, these methods do not utilize the temporal information for text detection in video.

2.1.2 Methods with Temporal Information

This section provides literature survey on the methods which uses temporal information for text detection like proposed methods.

Li et al (H. Li, Doermann, & Kia, 2000) proposed method for video text tracking based on wavelet and moments features. This method uses advantage of wavelet decomposition, spatial information provided by the moments with neural network classifier for identifying text candidates. Text block shape features are used to track the

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text in temporal frames. Huang et al. (Weihua Huang, Shivakumara, & Tan, 2008) proposed a method for scrolling text detection in video using temporal frames. This method uses motion vector estimation for detecting text. However, this method is limited to only scrolling text but not arbitrary orientation texts. Zhou et al. (J. Zhou, Xu, Xiao, Dai, & Si, 2007) exploit edge information and geometrical constraints to form a coarse-to-fine methodology to define text regions. Then candidate regions are labeled as connected components by morphological close operation and filtered by geometrical constraints. Based on the temporal redundancy, the text authentication and enhancement are implemented over multiple frames by using the text polarity consistency, overlapping text area and the stability of character stroke. However, the method is unable to deal with dynamic text objects. Mi et al. (Congjie et al., 2005) proposed a text extraction approach based on multiple frames. The edge features are explored with similarity measure for identifying text candidates. Wang and Chen's method (Y.-K. Wang & Chen, 2006) uses spatio-temporal wavelet transform to extract text objects in video documents. In the edge detection stage, a three-dimensional wavelet transform with one scaling function and seven wavelet functions is applied on a sequence of video frames. Then in the classification stage, the texture features, such as grey-level co-occurrence matrix, maximum probability, energy, and entropy, calculated from salience maps are input to a Bayes classifier to obtain final text regions.

Huang (X. Huang, 2011) detected video scene text based on the video temporal redundancy. Video scene texts in consecutive frames have arbitrary motion due to camera or object movement. Therefore, method performs the motion detection in 30 consecutive frames to synthesize motion image. Further video scene text detection is implemented in single frame to retrieve candidate text regions. Finally, the synthesized motion image is used to filter out candidate text regions and only keep the regions which have motion occurrence as final scene text. Zhao et al (Z. Xu et al., 2011)

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proposed an approach for text detection using corners in video. This method proposes to use dense corners for identifying text candidates. From the corners, the method forms region of text using morphological operations. Then the method extracts features, such as area, aspect ratio, orientation etc. for the text regions to eliminate false text regions. Finally, optical flow has been used for moving text detection. Liu & Wang (Xiaoqian Liu & Wang, 2012) proposed a method for video caption text detection using stroke like edges and spatio-temporal information. The color histogram is used for segmenting text information. Li et al (L. Li, Li, Song, & Wang, 2010) proposed a method for video text detection using multiple frames integration. This method uses edge information to extract text candidates. The morphological operation and heuristic rules are proposed to extract final text information from video.

Bouaziz et al. (Bouaziz, Zlitni, & Mahdi, 2008) proposed a similarity criterion to find text appearance based on frame differences. However, the similarity criterion requires a threshold to identify the sudden difference. Therefore, it may not work for different types of videos. In addition, the focus of the method is only on graphics text detection but not scene text detection. Tsai et al. (Tsai, Chen, & Fang, 2009) proposed a method for video text detection using edge and gradient information. Though the method uses temporal frames, its performance depend on edge images and the number of temporal frames.

Wu et al (Wu et al., 2015) proposed a new technique for multi-oriented scene text line detection and tracking in video. The method explores gradient directional symmetry and spatial proximity between the text components for identifying text candidates. To handle the multi-font and multi-sized text, the method proposed multi-scale integration by pyramid structure, which helps to extract full text lines. The text

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lines are tracked by matching sub-graphs of text components. The ability of the method is not tested on arbitrarily-oriented text and multi-script text lines in video.

In summary, though the methods used temporal information for text detection in video, the features used in the methods are sensitive to blur and distortion. It is true that blur occurs due to text movements or camera movements which is quite common in videos. Besides, most of the methods fix the constant number of temporal frames out of 25-30 frames per second. This constraint causes poor accuracy.

2.2 Deblurring Text images

Although the reviewed approaches achieved promising results compared to high-resolution scene text in uncontrolled environments remains very challenging. Presence of blur in video is one such effect that may occur in video during the process of capturing due to motion of text object or the motion of camera handler. In this section, some of the existing deconvolution models, particularly deblurring methods on text images will be reviewed.

When literature on blind deconvolution is reviewed, it is observed that most of the models proposed are for general image deblurring but not for images containing text in video or natural scene images. As a result, one can see only a few deblurring models related to text applications. For instance, Pan et al. (J. Pan et al., 2014) propose a simple yet effective L0-regularized prior based on intensity and gradient for text image deblurring. However, L0-norms are an np-hard problem which makes it expensive in terms of time complexity, and hence restricts its use in video applications. Cho et at (Cho et al., 2012) takes into account the specific properties of text images. This method extends the commonly used optimization framework for image deblurring to allow domain specific properties to be incorporated in the optimization process. Wang et al. (Y. Wang et al., 2008) proposed an alternating minimization algorithm for recovering

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images from blur and noise observations with total variation (TV) regularization which is good for edge preservation. However, one paper for scene text deblurring using text-specific multi-scale dictionaries by Cao et al (Cho et al., 2012). The objective of this method is to improve the visual quality of blurred images by applying a deblurring method. The method explores the combination of multi-scale dictionaries and an adaptive version of non-uniform deblurring method. The performance of the method depends on the size of the dictionaries and kernel estimation for different situations. There is a need for developing a new deblurring model, specifically for text in video and natural scene images.

2.3 Summary

The methods which are proposed based on connected component analysis; texture; edge/gradient and methods that use temporal information are reviewed. Based on analysis of existing methods, conclusion can be made that the followings are still major issues without perfect solution for text detection in video.

(1) Most of the current methods focus on horizontal caption texts for detection in video because the methods use advantage of characteristic of caption text, such as uniform color, high contrast, and uniform size. However, these constraints are not necessarily true for scene text in complex backgrounds. There is scope for developing a method which can detect both caption and scene text.

(2) The existing methods utilize the temporal frame information for enhancing text detection performance that is for false removal but not for detecting moving text in videos. In other words, the existing methods do not use the fact that text in video usually moves unidirectional with almost constant velocity. Therefore, the scope of the method is to detect static text rather than moving text in video.

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(3) Though the existing methods use multiple frames for text detection but not much attention has been given for automatically determining the number of temporal frames used. The methods generally assume the number of frames to be processed based on experimental results. The threshold fixed based on experiments may not work well for different dataset and situations.

(4) Since most of the existing methods use classifiers and large number of training samples for classification of text and non-text at pixels or component level or text line level. Therefore, the methods lose the ability of multi-script text detection in video. This limits generic ability.

The above demerits of existing methods is motivation to propose new methods, which are capable of detecting moving and static text as well as multi-oriented and multi-lingual text from videos accurately and efficiently, irrespective of text types, orientations and scripts.

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CHAPTER 3: A NEW HISTOGRAM ORIENTED MOMENTS DESCRIPTOR FOR MOVING TEXT DETECTION

From the previous chapter where detailed literature for detecting text from videos is reviewed, one can conclude that very few methods are designed for detecting graphics and scene text together and which is able to utilize the temporal information for finding the moving text. In this work, a new descriptor called Histogram Oriented Moments (HOM) for text detection in video is introduced, which is invariant to rotation, scaling, font, font size variations.

3.1 Introduction

This work proposes a new descriptor called Histogram Oriented Moments (HOM) for both static and moving text detection in video. As the proposed method is inspired by the work presented in (Minetto et al., 2013; Tsai et al., 2009; Wolf & Jolion, 2006) where the new descriptors were developed by referring a Histogram Oriented Gradients (HOG) for text detection and Histogram of Optical Flow for detecting human action, this method introduces a new descriptor based on moments for text detection in video. The main reason to choose moments for deriving this descriptor is that moments consider both spatial information as well as pixel values for estimating orientation in contrast to HOG which uses only gradient information for text detection. In this way, the HOM descriptor is different from the existing descriptors. The HOM finds dominant orientation for each overlapped block by performing histogram operation on moment orientation of each sliding window. The proposed method derives a new hypothesis based on dominant orientations as the numbers of orientations which move towards centroid of the connected component are larger than the number of orientations which move away from the centroid of the connected component to classify text and non-text components. The components which satisfy the above hypothesis are

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considered as text candidates while others are considered non-text candidates. Geometrical characteristics of text candidates are proposed for eliminating false text candidates. The proposed method explores optical flow properties of the text for detecting moving text.

3.2 Proposed Method

It is true that moments have been used for text detection successfully in literature (H. Li et al., 2000) because the moments have ability to capture unique features such as spatial information and structure of the components, which can distinguish text from non-text from the complex background of video. With this notion, the proposed method uses the second order moments for deriving new descriptor to estimate orientations which represents group of text pixels as HOG uses gradient orientations. The flow of proposed procedure can be seen in Figure 3.1.

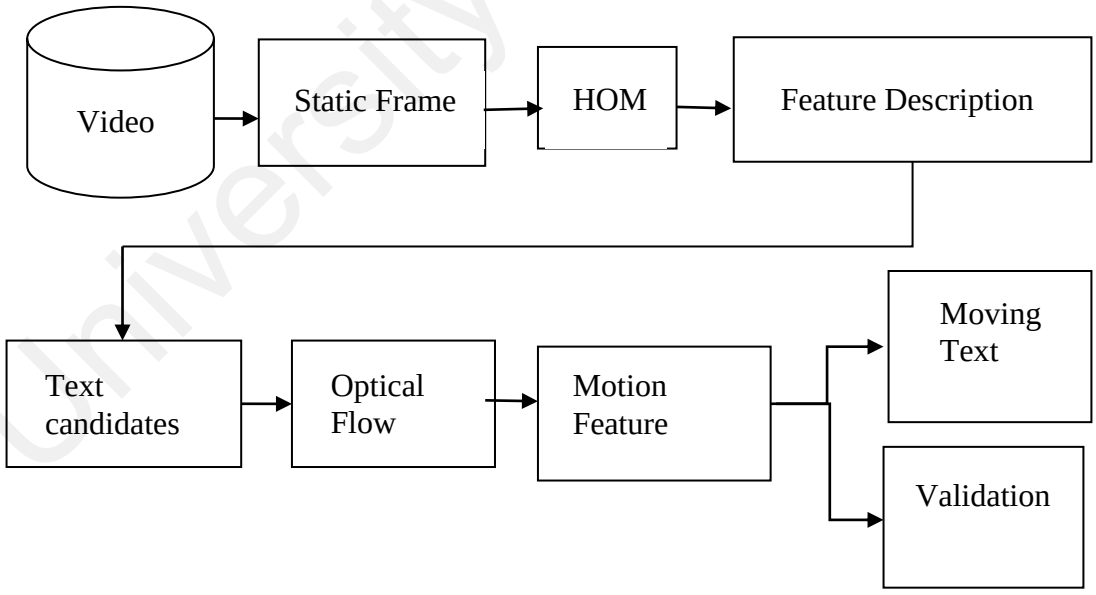

Figure 3.1: Steps of the proposed method

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3.2.1 HOM for Text Candidates Selection

For a given video, the proposed method select frame containing text as shown in Figure 3.2(a) where one can see different oriented text lines. The proposed method divides the whole frame into overlapped equal sized sub-blocks of size 8 × 8. For each overlapped block (size 8 × 8) in Figure 3.2(a) method determine second order moments as defined in equations (3.1)-(3.7). Figure 3.2(b) shows the moment image of input frame computed through second order moments. Figure 3.2(c) represents the orientations for highlighted block in Figure 3.2(b). Then the proposed method obtains dominant orientation for each block by performing histogram operation. That is, divide the entire range of orientation values into a series of orientation intervals—and then count how many values fall into each orientation interval. Histogram for the selected block is shown in Figure 3.2(d). The orientation which represent highest peak is considered as dominant orientation as shown in Figure 3.2(e) where the orientation represent the whole block. The final dominant orientations for all the blocks can be seen in Figure 3.2(f) where it is noted that all dominant orientations are representing edge pixels of the objects for the input frame in Figure 3.2(a). This is the advantage of the orientations given by moments as it gives high response for text pixels where there is a high contrast and low response for non-text pixels where there is a low contrast. This high response near text pixels will reflect as higher attraction of HOM orientations towards those components in the image. Based on this observation, a new hypothesis can be drawn that if the orientations of the component which move towards component (inside count) are larger than the orientations of the component which move away from the component (outside count) then the component is considered as text component else it is non-text component as shown in Figure 3.3. The proposed method eliminates non-text components using this hypothesis. The effect can be seen in Figure 3.3(e) where most of the non-text components are removed. This output is called text candidates.

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$$\theta(f) = 1/2 * \arctan(2\mu_{11}^{'}/(\mu_{20}^{'} - \mu_{02}^{'})) \quad (3.1)$$

Here μ_{pq} is central moment of the image *f(x, y)* drawn from,

$$\mu_{pq} = \sum_{x}\sum_{y}(x-\bar{x})^{p}(y-\bar{y})^{q} f(x,y) \quad (3.2)$$

In order to reduce the computational complexity, raw moments are used to generate 2nd order central moment rather than using the above equation. Required second order central moment can be directly drawn by:

$$\mu_{20}^{'} = M_{20}/M_{00} - \bar{x}^{2} \quad (3.3)$$

$$\mu_{02}^{'} = M_{02}/M_{00} - \bar{y}^{2} \quad (3.4)$$

$$\mu_{00}^{'} = M_{11}/M_{00} - \bar{x}.\bar{y} \quad (3.5)$$

Where $(\bar{x}, \bar{y})$ are centroids drawn from following:

$$\bar{x} = M_{10}/M_{00}, \ \bar{y} = M_{01}/M_{00} \quad (3.6)$$

Image raw moments can be define as the weighted average (moment) of the image pixels' intensities

$$M_{ij} = \sum_{x=1}^{N}\sum_{y=1}^{N} x^{i} y^{j} f(x,y) \quad (3.7)$$

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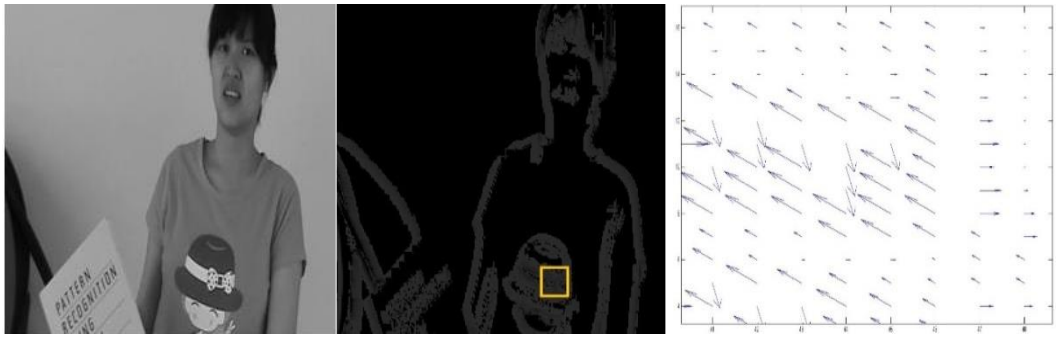
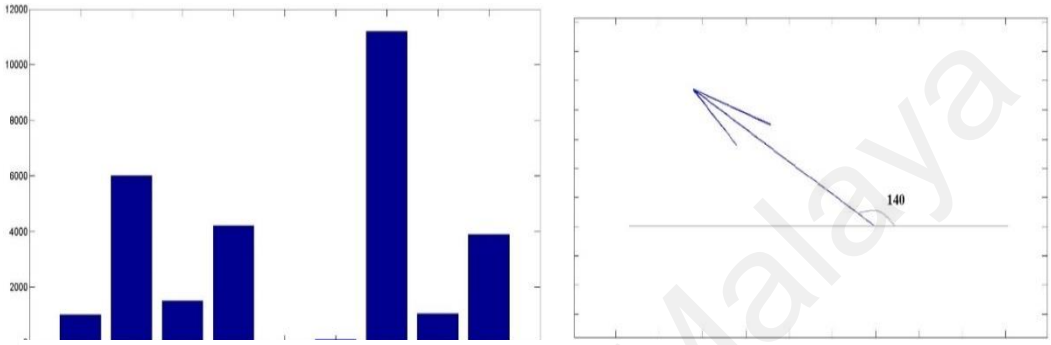
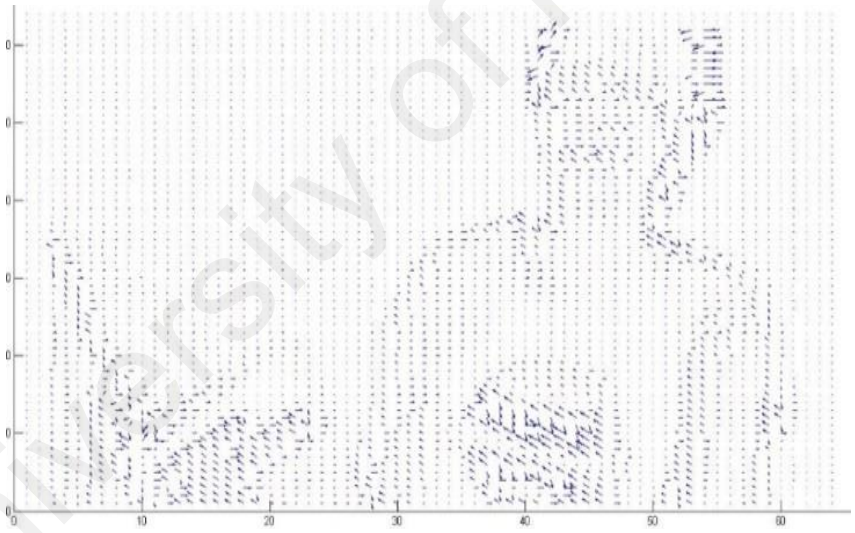


(a) Frame (b) Moment Image (c) Moment Directions of selected block



(d) Histogram of all pixels in a block (e) Resultant HOM direction



(f) HOM Directions

Figure 3.2: Orientations of the HOM descriptor

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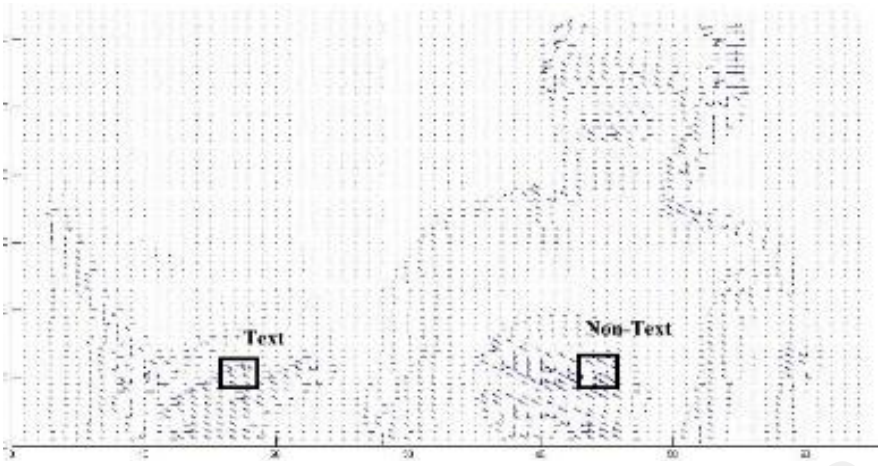
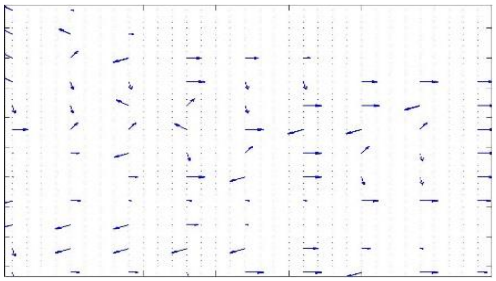
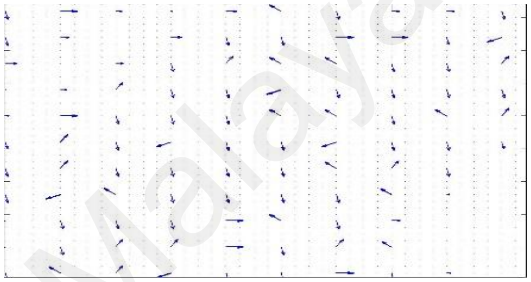


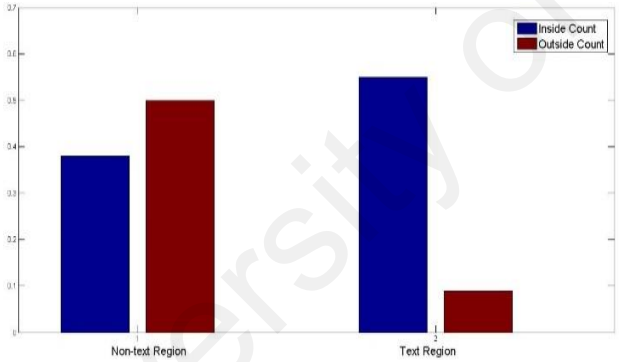
(a) HOM



(b) HOM directions for Non-text



(c) HOM directions for Text



(d) Inside and outside count for text and non-text

(e) Text Candidates

Figure 3.3: Text candidates selected by HOM descriptor

By looking at process and steps of the orientation estimation by moments, one can found that there is a similarity between Histogram Oriented Gradients (HOG) and HOM. This concept has been used for text detection in the past. Therefore, to show the performance of HOM over HOG, proposed method compile HOG with the same steps that of HOM. Figure 3.4 shows orientations given by HOG. As HOG involves gradient for orientation estimation for each pixel using sliding window over the image to extract features, the proposed HOM uses moments for orientation estimation over the image

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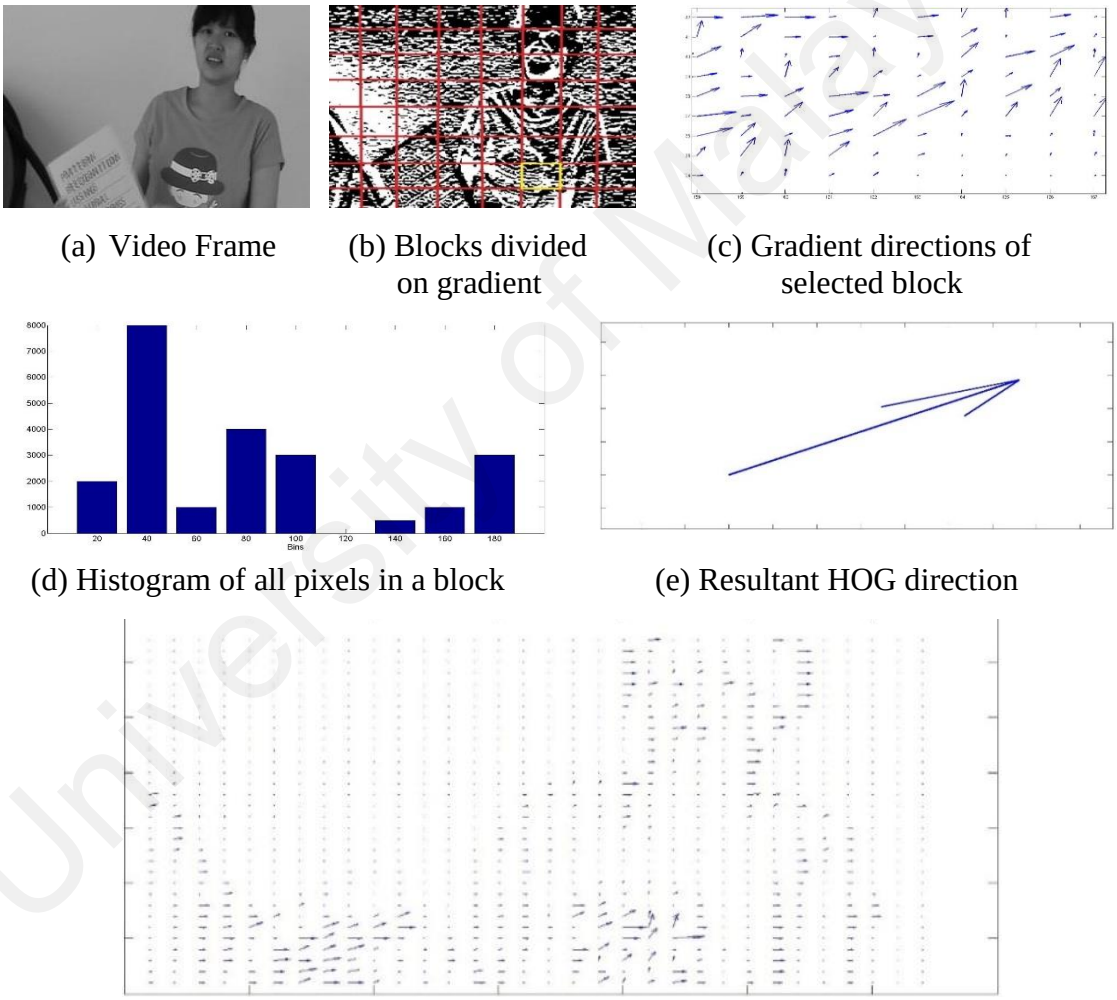
using sliding window to find dominant direction of text components. Therefore, in order to show effectiveness of the proposed HOM, the HOM is compared with HOG as shown in Figure 3.4 and Figure 3.5. For example, it is noticed from Figure 3.4 and Figure 3.5 that HOM is more effective compared to HOG because HOG gives more non-text components compared to HOM. This observation is found based on many video frames. The main reason of that is HOG considers only gradient directions while the HOM considers both spatial, as well as pixel values for finding orientations.



(a) Video Frame (b) Blocks divided on gradient (c) Gradient directions of selected block

(d) Histogram of all pixels in a block (e) Resultant HOG direction

(f) HOG Directions for all blocks

Figure 3.4: Orientations of HOG descriptor

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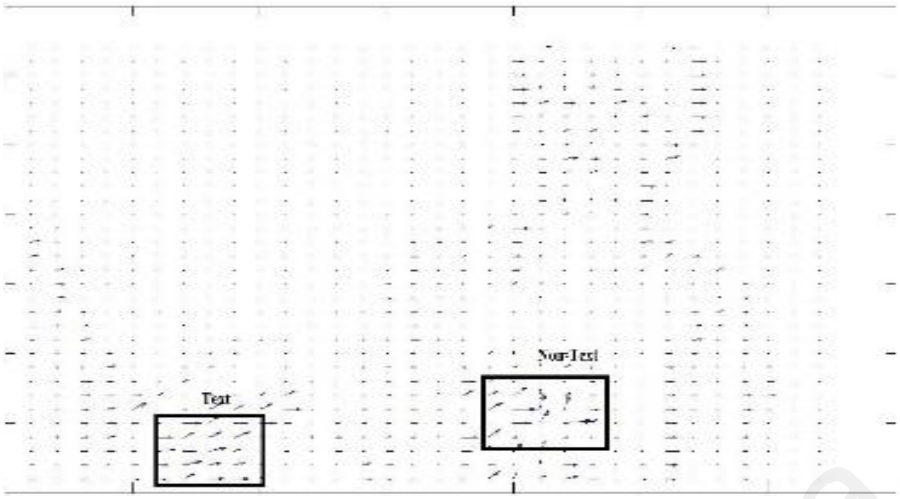
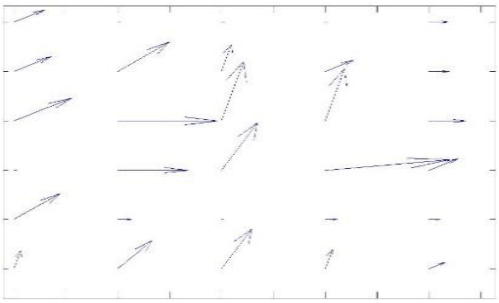
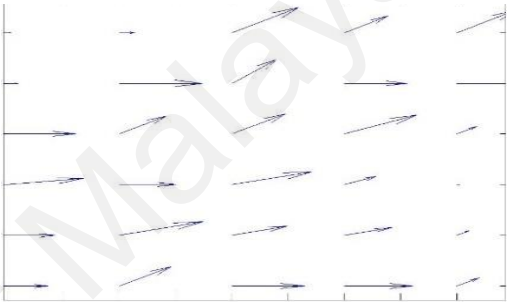


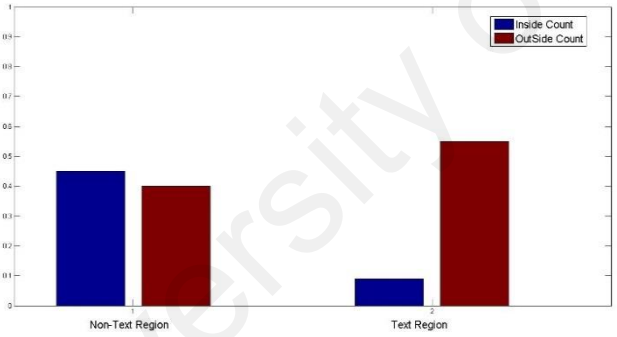
(a) HOG Directions



(b) HOG directions for Non-text



(c) HOG Directions for Text



(d) Inside and outside count for respective non-text (b) and text (c) block

(e) Text candidate

Figure 3.5: Effect of HOG descript for text candidate selection

3.2.2 Text Candidates Verification

Figure 3.3(e) shows that the HOM alone is not sufficient to remove false text candidates due to variation in background and resolution. The proposed method proposes two features, based on structure of text candidates that are dense corners and edge density.

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Dense corners provides cue for the text information in the images. Therefore, the proposed method explores corners for detecting text candidates in the images. A corner can be defined as the intersection of two edges or a point where there are two dominant and different edge directions in a local neighborhood of the point. The proposed method uses Harris corner detector (Harris & Stephens, 1988) to extract the corner points. The Harris method uses algorithm that depend on the eigenvalues of the summation of the squared difference matrix (SSD). The eigenvalues of an SSD matrix represent the differences between the surroundings of a pixel and the surroundings of its neighbors. The larger difference between the surroundings of a pixel and those of its neighbors, the larger the eigenvalues, which results in corners.

Similar to corners, edges are edge density is used here to remove small non-text components. For a given window, an edge density feature measures the average edge magnitude in a sub-region of the window. Let *W(u,v)* be a window and *e(u,v)* be the edge magnitude of the window. For a sub-region r with the left-top corner at *(u1, v1)* and the right-bottom corner at *(u2, v2)*, the edge density feature is defined as

$$f = \frac{1}{a_r} \sum_{u=u_1}^{u_2} \sum_{v=v_1}^{v_2} e(u,v) \tag{3.8}$$

where a_r is the region area, $a_r = (u_2 - u_1 + 1)(v_2 - v_1 + 1).$ A block is rejected if the edge density is smaller than the fixed threshold. It is known fact that dense corner and edge density are high for the text candidates compared to non-text candidates. The effect can be seen in Figure 3.6(c) where almost all false text candidates are removed. The final text detection results are shown in Figure 3.6(d) where one can see bounding boxes for the text lines. The thresholds for the above rules are determined based on experimental study.

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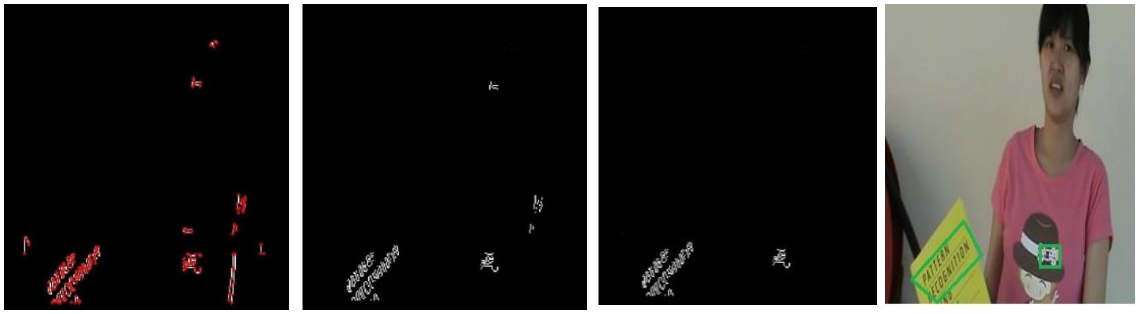

(a) (b) (c) (d)

Figure 3.6: (a) Corners are detected for the text candidates, (b) and (c) represents outputs when low dense corners and low edge density edges are rejected (d) Final text detection result are shown

3.2.3 Moving Text Detection

This section focuses on detecting moving text using temporal frames. The proposed method proposes optical flow and its properties to determine moving text. It is valid that text in video moves with same velocity and single direction especially, graphics text. This is the key property of moving text which is exploited it this work. As this work is inspired by the work presented in (Bruhn, Weickert, & Schnörr, 2005) where optical flow is used globally, as well as locally for tracking objects of arbitrary movements, the proposed method uses the same concept for tracking text in video in this work. The proposed method uses optical flow globally and locally to overcome the problem of moving background objects. Global optical flow helps in differentiating moving background objects from the graphics text while local optical flow assists in estimating constant velocity and direction of the texts. The proposed method use the combined global-local spatial approach presented in (Bruhn et al., 2005), which tries to combine the local Lucas-Kanade method and global Horn-Schunk method advantages. Let us first reformulate the previous approaches as them. Here, *(u,v)* are displacement field called optical flow, using the notions:

$$w := (u, v, 1)^T \tag{3.9}$$

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$$|\nabla w|^2 := |\nabla u|^2 + |\nabla v|^2 \tag{3.10}$$

$$\nabla_3 f := (f_x, f_y, f_t)^T \tag{3.11}$$

$$J_p(\nabla_3 f) := K_p * (\nabla_3 f \nabla_3 f^T) \tag{3.12}$$

Lucas-Kanade method minimizes the quadratic form,

$$E_{LK}(w) = w^T J_p(\nabla_3 f) w \tag{3.13}$$

While Horn-Schunk technique minimizes the functional,

$$E_{HS}(w) = (w\_J_0(\nabla_3 f)w + \alpha|\nabla w\ |_2)dxdy \tag{3.14}$$

This terminology suggests a natural way to extend the Horn-Schunk functional to desired CLG functional. The proposed method simply replaces the matrix $J_0(\nabla_3 f)$ with some integration scale $\rho > 0$. Thus, it minimize the functional,

$$E_{CLG}(w) = \int_{\Omega} (w^T J_p(\nabla_3 f) w + \alpha |\nabla w|^2) dxdy \tag{3.15}$$

Its minimizing flow field *(u,v)* satisfies the Euler-Lagrange equations. This replacement is hardly more complicated than the original Horn-Schunk Equations. More detailed about this algorithm can be found in (Bruhn et al., 2005). The proposed method extracts the optical flow feature for every consecutive frame, in order to preserve the spatial-temporal information. Sample of optical flow computed over frames are shown in Figure 3.7.

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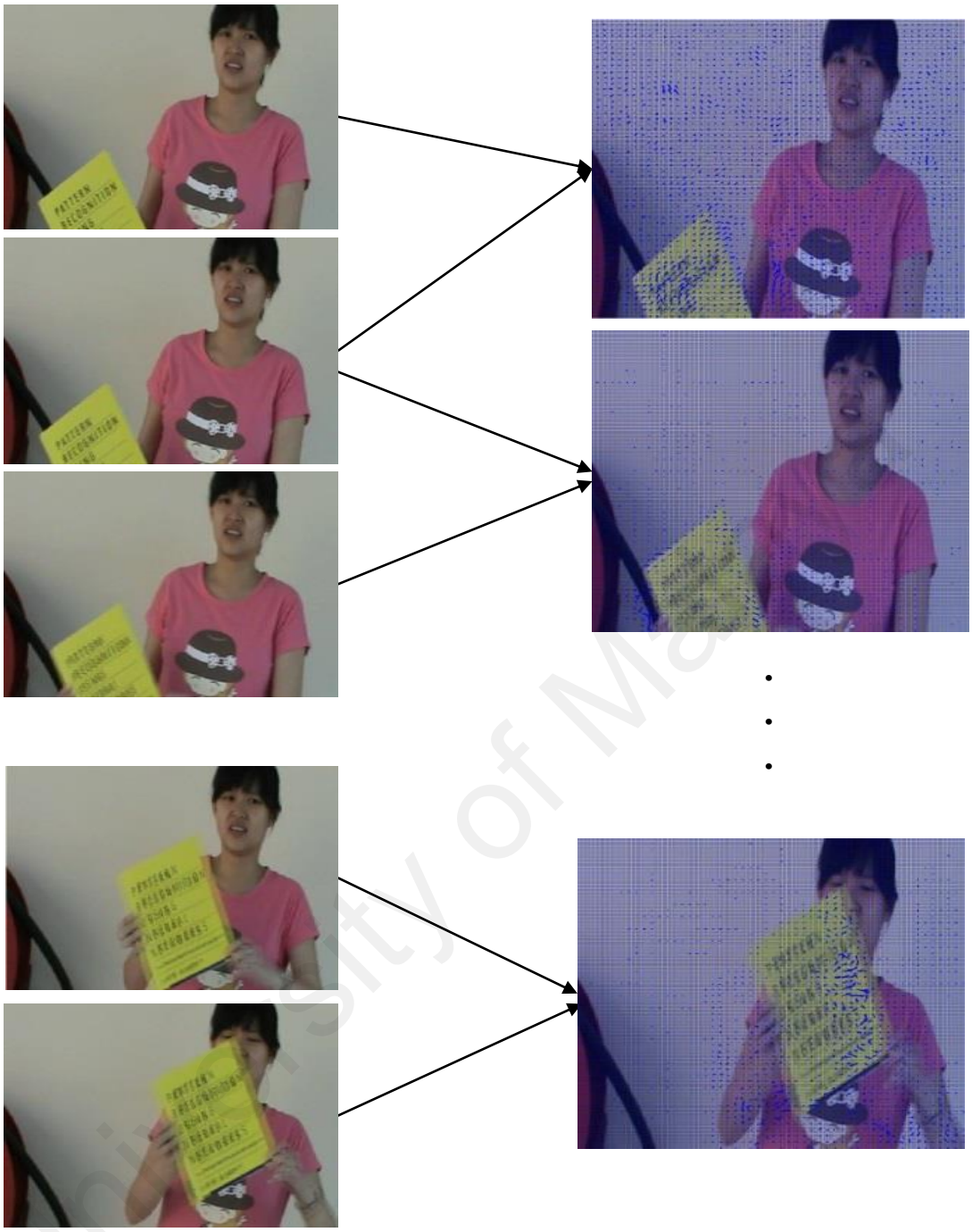
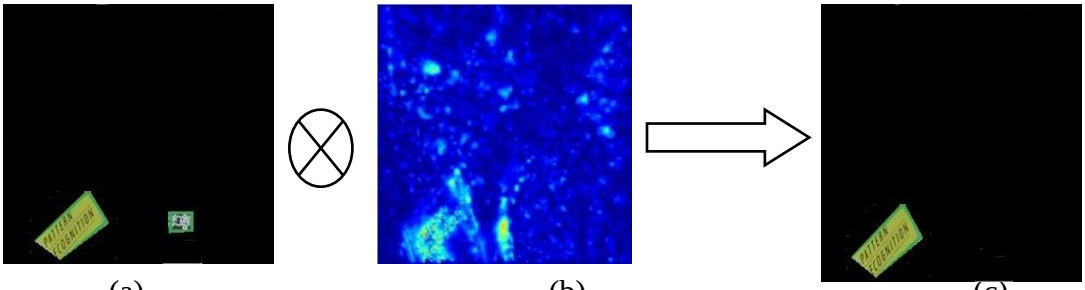


Figure 3.7: Optical flow vectors marked over video frames

The combination of motion features with the detected text candidates by the previous section is used to detect moving text. Since the previous step gives text candidates for every frame, the method uses motion feature corresponding to text candidates to identify the moving texts as shown in Figure 3.8.



(a) (b) (c)

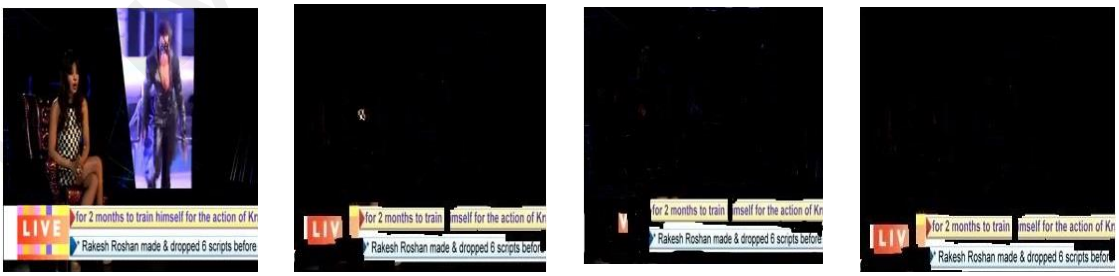
Figure 3.8: (a) Detected Text region multiplied with (b) optical flow intensity fields can classifies the moving text region in (c)

The velocity and direction feature are calculated as follows: Let *(u, v)* be the optical flow vectors, then direction (θ) and velocity (vel) can be defined as:

$$\theta = \tan^{-1}(v/u) \tag{3.8}$$

$$vel = \sqrt{u^2 + v^2} \tag{3.9}$$

When velocity and direction changes drastically, the proposed method stops process of estimating motion with optical flow method. According to the experiments, for almost all the cases, the method uses less than 10 frames for moving text detection. Figure 3.9 illustrates one sample example for moving text detection.



(a) (b) (c) (d)

Figure 3.9: (a) Input frame (b)-(d) shows intermediate results of moving text detection

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3.3 Experimental Results and Discussion

All experiment are executed over the system Windows XP Intel core i5 with 6GB RAM. To evaluate the effectiveness of the proposed descriptor, comparison has been made with latest and well known existing methods: Liu et al. (C. Liu et al., 2005), Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010) and Zhao et al. (Z. Xu et al., 2011), which does not utilize temporal information (uses single frame) for text detection from video. Liu et al. (C. Liu et al., 2005) proposed a method for text detection in video using texture features and k-means clustering. These methods are good for caption text but not for combinational graphics and scene text. Similarly, Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010) proposed an improved method which detects both graphics and scene text in video based on the combination of wavelet and color features. Zhao et al. (Z. Xu et al., 2011) uses the dense corners and other features to detect text in video as well as in single frame.

The proposed method is also getting compared with the methods which use temporal frames for text detection. Mi et al. (Congjie et al., 2005) which uses multiple frames for text detection, Huang (X. Huang, 2011) which uses motion vector for detecting text in video.

3.3.1 Dataset

To evaluate the performance of the proposed descriptor, a benchmark database ICDAR 2013 video (Karatzas et al., 2013) is used which is available publicly. This data contains 15 videos captured at different rates and different situations. In addition, the video contains text of different types such as different scripts, fonts, font size and orientations. In the same way, authors own dataset of size 1000 video is also created at 30 frames per second. This data is collected from different sources, namely, CNN, CNBC, NDTV news channels ESPN, FOX, Ten sports, Star sports channels. Own

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dataset videos usually contain significant variations in font styles, contrast, font sizes and complex background variations. For example News channels videos like CNN, CNBC or NDTV have combination of large number of scene text and caption text that can be moving text (rolling news at bottom of screen). Whereas sports channels like ESPN, FOX, Ten sports, Star sports have more number of scene text with lot of moving text in the presence of small number of caption text. The proposed method believes this data is good enough to cover all possible variations of texts and situations. In total 1015 videos are considered for evaluating the proposed descriptor. Few of the sample images are shown in Figure 3.10.

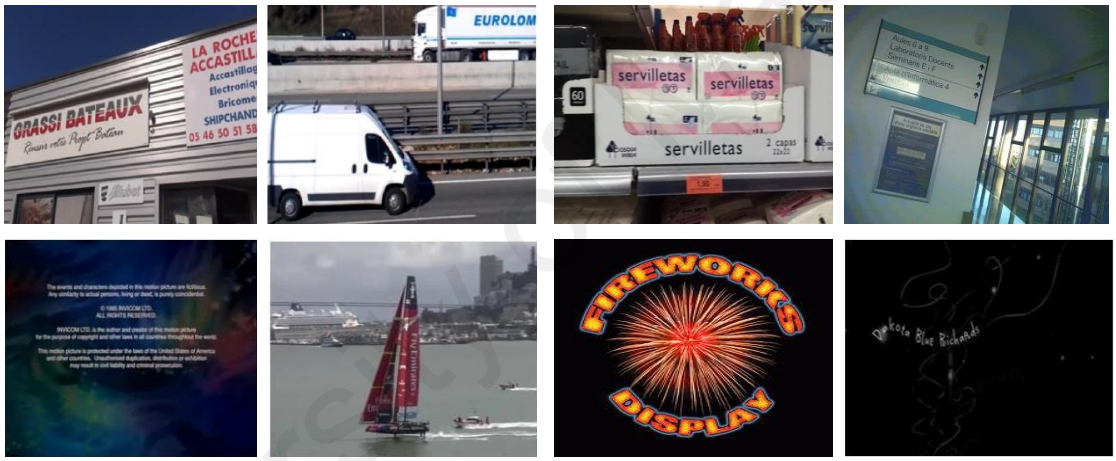

Figure 3.10: Sample images from dataset considers

3.3.2 Description of Measures

Three standard measures are considered, namely, recall, precision and F-measure for measuring the performance of the proposed technique. The proposed evaluation system follows the standard evaluation scheme as given in the ICDAR 2013 robust reading competition. Note that the measure proposed in (Karatzas et al., 2013) requires words segmentation because the ground truth is generated for words but not text lines. Since video suffer from low contrast, word segmentation is not easy as word segmentation in natural scene images. In order to use the standard measures, the ground truths of words is combined and transformed into text lines for calculating the measures. For all the

experimentations in this work, measures are calculated at text lines with the same measures. Specifically, the measures are defined formally as follows. A match m_p between two rectangles (detected and ground truth) is defined as the area of the intersection (Figure 3.11 shaded area) divided by the area of the minimum bounding box containing both rectangles, an example is shown in Figure 3.11.

Figure 3.11: Example of matching between detected block (red) and ground truth (yellow)

So the best match $m(r;R)$ for a rectangle *r* in a set of rectangles *R* is defined as

$$m(r,R) = \max\{ m_p(r;r') \mid r' \in R\} \tag{3.10}$$

This is defined to find the closest match in the set of ground truth targets for each rectangle in the set of estimates. Then Precision and Recall are defined as

$$\textit{Precision (P)} = \frac{\sum_{r_e E_s} m(r_e;T_r)}{|E_S|} \tag{3.11}$$

$$\textit{Recall (R)} = \frac{\sum_{r_t \in T_r} m(r_t;E_S)}{|T_r|} \tag{3.12}$$

Where T_r and E_S are the sets of targets (ground truth) and estimated boxes, respectively. These two measures are combined to form a single F-measure or F-score: *f* with a parameter α. The α is set to 0.5 to give precision and recall an equal weight while testing on ICDAR 2013 data set as stated by (Karatzas et al., 2013) and 0.8 for authors own dataset. The reason for selecting higher α parameter for this experiments is to create stricter boundary for evaluation,

$$f = \frac{1}{\frac{\alpha}{P} + \frac{1-\alpha}{R}} \tag{3.13}$$

In addition to these measures, Average Processing Time (APT) per frame is also used as a measure to evaluate time efficiency for text detection.

3.3.3 Experiment on ICDAR 2013 Video

Sample qualitative results of the proposed and existing methods for text detection from single frames are shown in Figure 3.12 where one can notice that the proposed method detects text line well for the multi-oriented text with different backgrounds. The methods proposed by Liu et al. (C. Liu et al., 2005), Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010) and Zhao et al. (Z. Xu et al., 2011) detect text lines with missing text and more false positives because these methods are sensitive to orientations. These existing methods focus much on horizontal text detection but not multi-oriented text detection. Therefore, the methods give poor results for the input images in Figure 3.12. On the other hand, the proposed descriptor is developed for both horizontal and non-horizontal text detection in video. Quantitative results of the proposed and existing methods are reported in Table 3.1 where it is found that the proposed method outperforms the existing methods in terms of recall, precision, F-measure and average processing time. One can observe from Table 1 that recall of the

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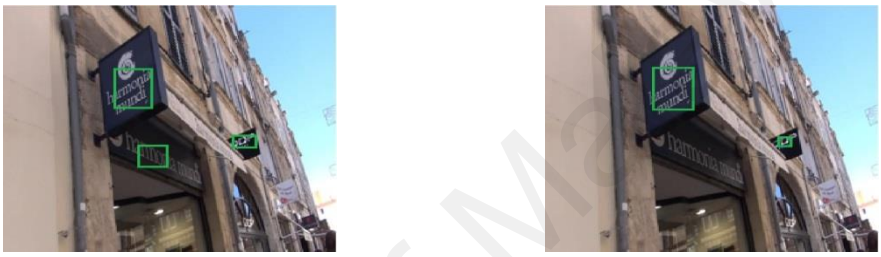
proposed is close to the existing method while precision shows significant difference compared to existing methods. This shows the proposed descriptor detects text well without much false positives.

(a) Input Frame (b) Proposed Method (c) (Z. Xu et al., 2011)



(d)(Palaiahnakote Shivakumara, Phan, & Tan, 2010) (e)(C. Liu et al., 2005)

Figure 3.12: Sample results for proposed and existing methods when tested over individual frames

Table 3.1: Performance on ICDAR2013 when tested over individual frames

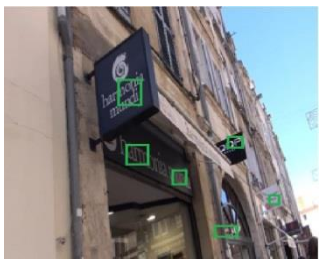
Method	Recall	Precision	F-Score	APT(s) Per Frame
Proposed Method	0.74	0.82	0.78	2
(Z. Xu et al., 2011)	0.71	0.69	0.70	2.5
(Palaiahnakote Shivakumara et al., 2010)	0.72	0.78	0.75	2.3
(C. Liu et al., 2005)	0.68	0.67	0.67	2

Similarly, the proposed and existing methods are tested on temporal frames for text detection. The qualitative and quantitative results of the proposed and existing methods are shown in Figure 3.13 and Table 3.2, respectively. Figure 3.13 and Table 3.2 show that the proposed method utilizes temporal frames well for text detection as it detects text lines well compared to existing methods. From Tables 3.1 to 3.2, recall improves slightly compared to without temporal frames experiments because temporal information helps us to locate text properly for the complex backgrounds. This shows

that the proposed optical flow based method for moving text detection helps in improving overall accuracy of the methods. However, according to F score, the proposed method gives consistent results for both temporal and without temporal frames.

(a) Input Frame

(b) Proposed Method



(c) (Z. Xu et al., 2011) (d) (Congjie et al., 2005), (e) (X. Huang, 2011)

Figure 3.13: Sample results for proposed and existing methods when temporal information is used

Table 3.2: Performance on ICDAR2013 with temporal information

Method	Recall	Precision	F-Score	APT(s) Per Frame
Proposed Method	0.76	0.79	0.77	2.3
(Z. Xu et al., 2011)	0.69	0.65	0.7	2.6
(Congjie et al., 2005)	0.73	0.72	0.77	2.3
(X. Huang, 2011)	0.7	0.69	0.69	2.8

3.3.4 Experiment on Author's Dataset

Sample qualitative and quantitative results of the proposed and existing methods using single frame are shown in Figure 3.14 and Table 3.3, respectively. It has been observed from Figure 3.14 and Table 3.3 that the proposed method performs better for the different orientations text with background images while existing methods either

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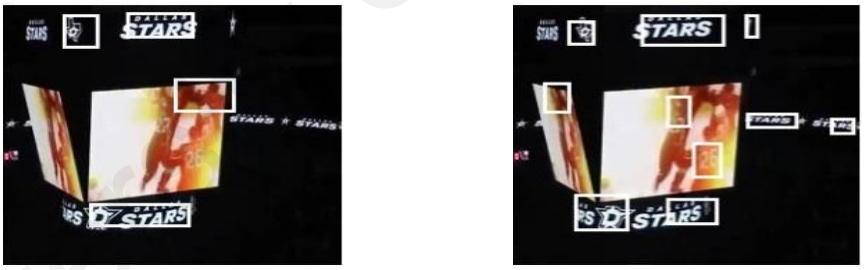
miss text information or give more false positives. When created dataset is compared with ICDAR 2013 video, this dataset is huge and has plenty of variations. As for this dataset no ground truth is available, so manual counting of recall and precision is made with stricter α value 0.8. For this dataset, the proposed descriptor gives better results than existing methods can give, in terms of recall, precision, F-measure, as well as average processing time. The main reason is that the proposed descriptor does not involve expensive operations such as connected component analysis which is part of the existing methods to improve the accuracy.

(a) Input Frame (b) Proposed Method (c) (Z. Xu et al., 2011)



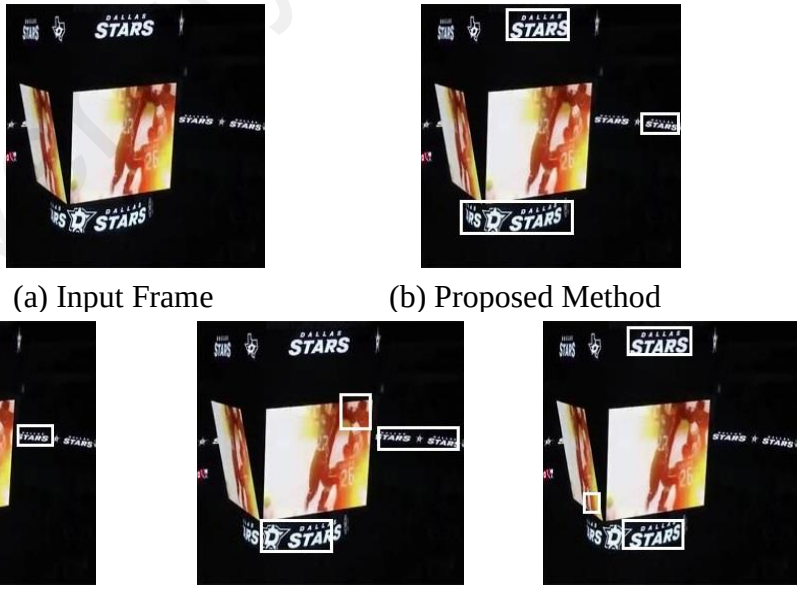
(d)(Palaiahnakote Shivakumara et al., 2010) (e)(C. Liu et al., 2005)

Figure 3.14: Sample results for proposed and existing methods when tested over individual frames

Table 3.3: Performance on Author's dataset when tested over individual frames

Method	Recall	Precision	F-Score	APT(s) per Frame
Proposed Method	0.8	0.84	0.82	2
(Z. Xu et al., 2011)	0.74	0.8	0.76	2.5
(Palaiahnakote Shivakumara et al., 2010)	0.71	0.82	0.76	2.2
(C. Liu et al., 2005)	0.7	0.65	0.67	2.1

In the same way, experiments for the temporal frames is also conducted to detect moving text in video as shown in Figure 3.15 and the results are reported in Table 3.4. It is noticed that the results of temporal frames has been increased compared to the results of single frames. This is because the dataset is large and the proposed method utilizes optical flow properties for improving text detection performance. In summary, the proposed new descriptor is good enough to handle temporal frames and single frames as it achieves better accuracy compared to existing methods.



(a) Input Frame (b) Proposed Method

(c) (Z. Xu et al., 2011) (d) (Congjie et al., 2005) (e) (X. Huang, 2011)

Figure 3.15: Sample results for proposed and existing methods for Scene text when temporal information used

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Table 3.4: Performance for scene text with temporal information

Method	Recall	Precision	F-Score	APT(s) Per Frame
Proposed Method	0.86	0.88	0.87	2.3
(Z. Xu et al., 2011)	0.73	0.75	0.73	2.6
(Congjie et al., 2005)	0.81	0.8	0.80	2.4
(X. Huang, 2011)	0.78	0.77	0.77	3.2

Based on the experimental results on standard dataset and authors dataset it can be concluded that the proposed method is competent to existing methods. However, there are some limitations as follows. The performance of the proposed method may degrade when a video contains text with arbitrary movements because the scope of the proposed method is limited to unidirectional moving text detection.

3.4 Summary

In this work, a new descriptor HOM is presented for both text detection from single frame and moving text detection in video. The proposed method explored second order geometric moments for deriving a new descriptor to exploits the strength of moments, such as spatial information and pixel values. This results in dominant orientation for each sliding window over an input frame. Next introduced a new hypothesis based on orientations of the moments to identify text candidates. False text candidates are removed by using dense corners and edge density of the text candidates. Optical flow with velocity and direction are explored for moving text detection. Experimental results on benchmark dataset, ICDAR 2013 and authors data show that the proposed method outperforms the existing methods for all measures i.e. recall, precision, F-Score and average processing time. Besides, experimental results shows that the proposed method is independent of orientation, data, fonts and font size. In this work after detecting text regions over individual frames, the proposed method utilizes the optical flow

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information to categorize the moving text region and for validating the text regions. The same temporal information will be explored for text candidates in next chapter.

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CHAPTER 4: MOTION ESTIMATION BASED METHOD FOR MULTI-ORIENTED MOVING TEXT DETECTION

In the previous chapter temporal information is used to identify the moving text from already detected text region from HOM feature. In this chapter, temporal information will be explored for detection of moving text from videos. Detection of moving text of different orientations in video is challenging because of low resolution and complex background of video. In this work, a method is proposed based on motion vectors to identify the moving blocks which have linear and constant velocity. The proposed method introduces a new criterion based on gradient direction of pixels in text candidates to remove false text candidates which results in potential text candidates. Then the proposed method performs region growing to group the potential text candidates which outputs text lines. The proposed method is tested on both static and moving text video to evaluate the performance in terms of recall, precision, F-measure, misdetection rate and time. The results are compared with the well-known existing methods to show effectiveness of the proposed method.

4.1 Introduction

Video containing moving caption text has a special property that is text will move with specific velocity for making it easily readable by viewers. So mostly if text is static then velocity of motion is zero and if text is moving then it will have some constant velocity. These observations lead us to utilize the motion pattern of objects present in videos for detecting moving text. In this work, a new method is presented which would be able to detect both moving scene and graphics text together independent to orientation. As this work is motivated by the work presented in (Congjie et al., 2005; H. Li et al., 2000; Minetto, Thome, Cord, Leite, & Stolfi, 2011) for text detection and tracking using wavelet, moments and motion vectors, the proposed

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method propose to use motion vectors with moments to identify text candidates. Gradient directional features are explored for the text candidates to identify potential text candidates. Then region is used for each potential text candidates to group them into text line of any orientation. Though the multi-oriented text detection in video have been addressed in (Palaiahnakote Shivakumara et al., 2014; Palaiahnakote Shivakumara, Phan, & Tan, 2011), the methods do not consider temporal information for text detection and their scope is limited to text detection from single frame in contrast to the proposed method. The main advantage of the proposed method is that it is capable of detecting both static and dynamic in video. The contribution is to use of motion vectors and moments in a novel way for detecting moving multi-oriented text regardless of whether text is caption or scene text.

4.2 Proposed Method

Text motion in video is one of the three types: static which does not have any motions, simple linear motion (for example, scrolling movie credits) and complex which may have non-linear motion (for example zooming in and out, rotation, or free movement of scene text). As per review, most of the videos contain first two cases and video having arbitrary text moments is rare. This work is targeting to detect the linear and arbitrary moving text. The flow chart of the proposed method is shown in Figure 4.1.

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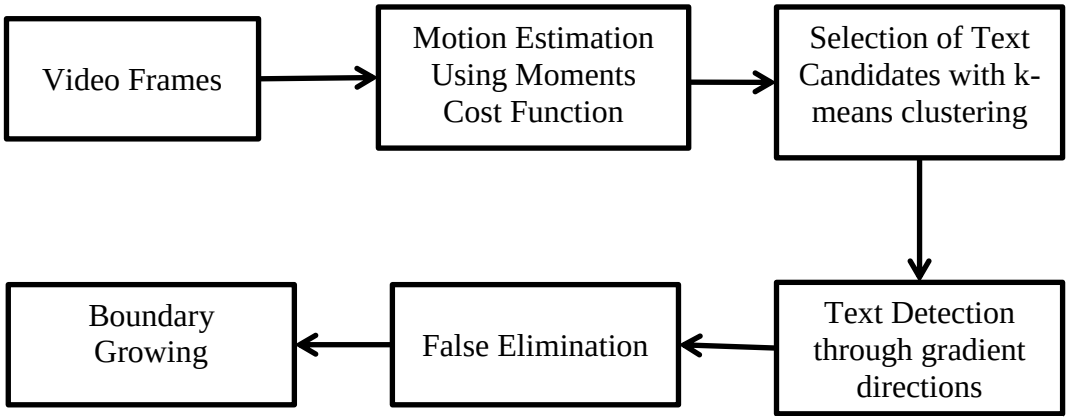

Figure 4.1: Flow chart of the proposed method

As motivated by the ability of motion vector estimation techniques proposed in (X. Huang, 2011; R. Li, Zeng, & Liou, 1994) for tracking moving objects with fast and efficient searching technique, the proposed method offers the same motion estimation with new three step search method for estimating the motion linearity of the blocks to identify the possible text blocks. The moments are proposed for identifying probable text blocks. When the gradient direction (Epshtein et al., 2010) of character components are studied, it is noted that most of the gradient direction of pixels, outer contour of character components moves into the character and few move away from the character. It can also been observed from Figure 4.2. This observation motivates us to propose a rule for identifying potential text candidates from the text candidates. Then in order to extract multi-oriented text line, region growing method is used as proposed in (Palaiahnakote Shivakumara et al., 2014) for text detection in individual frames.

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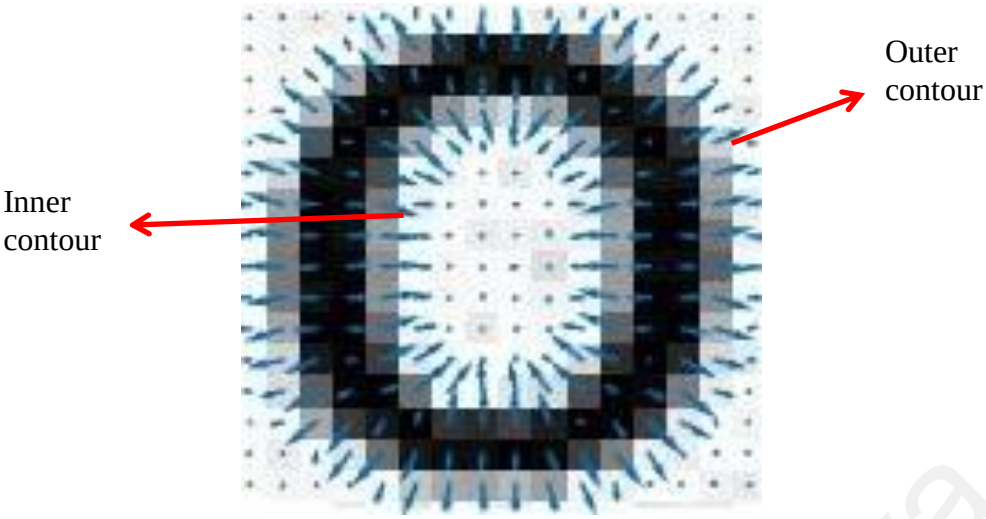


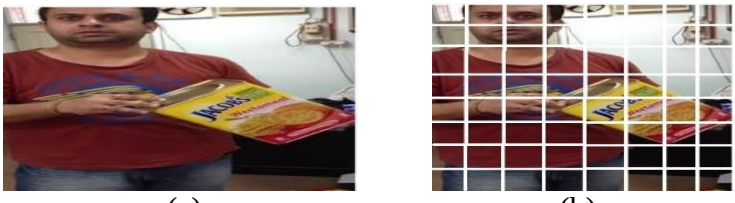
Figure 4.2: Gradient direction of a character showing outer contour

4.2.1 Motion Vector Estimation

Each frame of 256×256 pixels shown in Figure 4.3(a) is divided into sub-blocks of 8×8 sized block in non-overlapping fashion as shown in Figure 4.3(b). Each block is analyzed with motion vector estimation to find same motion, no motion and arbitrary moving text in video (R. Li et al., 1994). For each block in Figure 4.3(b), the proposed method computes moments as defined below:

$$moment_{p,q} = \sum_{0}^{N}\sum_{0}^{N}(x-\mu_x)^p(y-\mu_y)^q f(x,y) \qquad (4.1)$$

where central geometric moment of order p, q for each pixel $f(x,y)$ of image is computed with corresponding mean μ . N shows size of image.



(a) (b)

Figure 4.3: Text block division: (a) Input first frame, (b) blocks division

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Then a new three steps search is used as proposed in (R. Li et al., 1994) in order to find matching block and motion in the successive frames, the range of search is 3-level neighbor pixels for each pixel as shown in Figure 4.4.

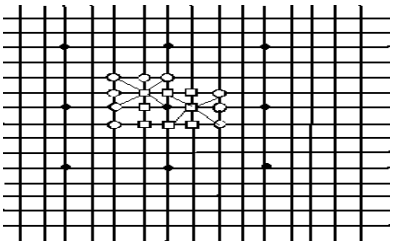

Figure 4.4: Search area for motion estimation through three steps search method

The proposed method finds difference of the moment of each block with the neighbor blocks in the adjacent frame to find matching block. Then Block Distortion Measure (BDM) is set to certain threshold to find probable match in the search area shown in Figure 4.4. For instance, for each video sequence, say first frame (F1) and second frame (F2) the motion is estimated with the cost (BDM) calculated by the difference among block moment:

$$\cos t(i, j) = \sum_{i=1}^{M} \sum_{j=1}^{N} momentF1(i, j) - momentF2(i+u, j+v) \qquad (4.2)$$

where M and N denote size of the block.

Equation (4.1) represents the difference of moment of each block *(i, j)* in frame1 with relative block *(i+u, j+v)* in next frame2. Moments are computed using Equation (4.1). In Figure 4.5, position of text in each frame is moving in same direction for all shown frames. Even if text moves in arbitrary direction it will be same for few limited frames. This can be determined with the help of moment of those blocks which will remain same for next few frames. In this way, the proposed method applies iterative procedure till the motion cost remain same for consecutive frames to extract moving text blocks which is the converging criteria to stop the procedure.

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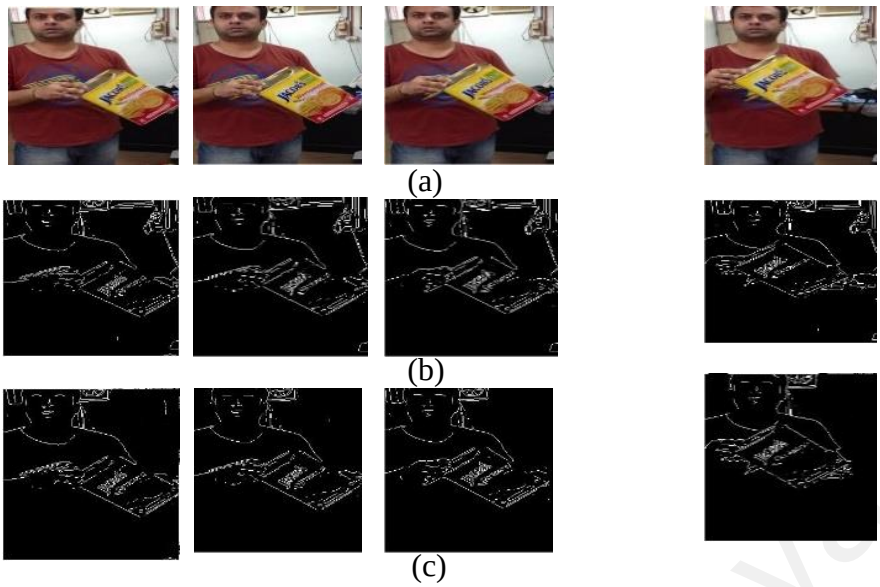

Figure 4.5: Illustration for text movements: (a) Video frames, (b) Edged image of each frame, and (c) text movements can be noticed

4.2.2 Selection of Text Candidates

The above process gives moving blocks which are the possible dynamic text blocks. Moment behavior at text region is utilized for probable text candidate selection. It is observed that the moments give higher value for text components and low value for non-text components. Therefore, k-means clustering is used wth k=2. The cluster that gives high mean is considered as a text cluster as shown in Figure 4.6(b) where one can see few non-text edge components are removed compared to Figure 4.6(a). This output is called text candidates. However, due to complex background and low resolution of video, Figure 4.6(b) still contains few non-text components.

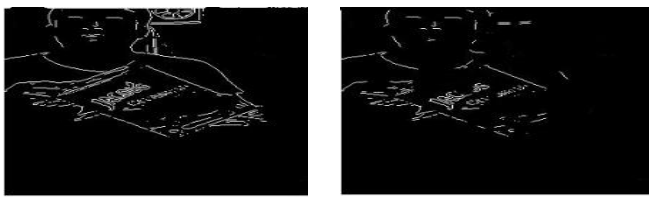

Figure 4.6: Text candidate selection: (a) Moving text with edge components, (b) Text candidates identified

4.2.3 Text Detection

It is noticed from the results in Figure 4.6 (b) that text candidate selection misclassifies non-text candidates as text candidates due to complex background and low resolution of video. To eliminate such false text candidates, proposed method proposes to use the gradient direction of each edge components based on the observation that most of gradient direction of outer contour pixels of edge component move towards characters centroid and few pixel gradient direction move away from the character centroid (Epshtein et al., 2010). This is illustrated in Figure 4.7.

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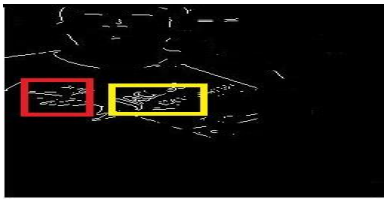
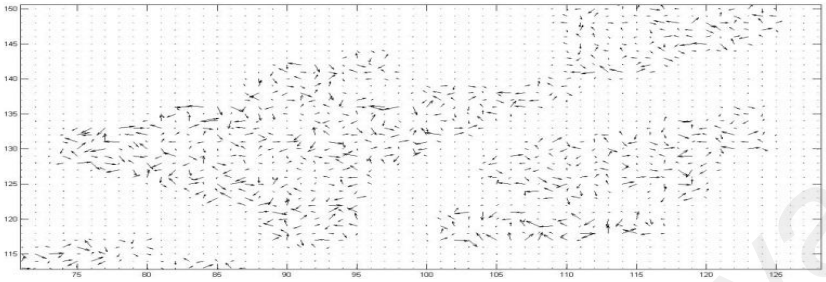
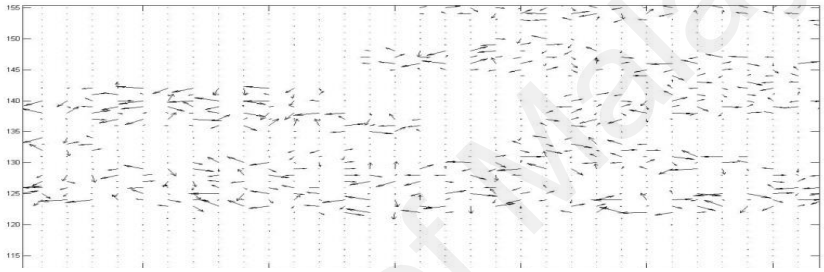


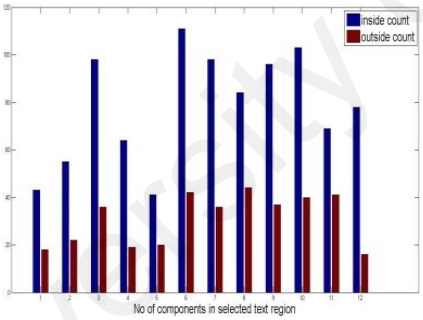
(a) Candidates which represent text is marked by yellow rectangle and candidates which represent non-text is marked by red rectangle



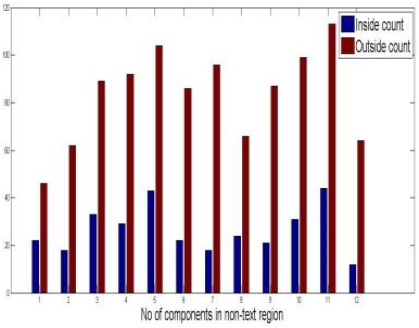
(b) Gradient directions for Text region marked in (a)



(c) Gradient directions for non-text region marked in (a)



No of components in text



No of components in Non-text

(d) Number of directions which go inside the components and away from the component

Figure 4.7: False text candidate removal using gradient directions

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(a) (b) (c)

Figure 4.8: Text representatives extraction: (a) Effect of gradient direction, (b) Effect of edge density, (c) Text representatives

The proposed method uses this criterion to eliminate false text candidates as shown in Figure 4.8(a). Further, edge density is used to remove small non-text components as shown in Figure 4.8(b), and finally edge components in Sobel edge image of the input first frame are restored corresponding to potential text candidates, which are called text representative as shown in Figure 4.8(c).

(a) (b)

(c) (d)

Figure 4.9: Text detection: (a) Mask operation to connect potential text candidates, (b) Boundary grown mask (c) Text lines edges inside final boundary grown Mask and (d) Text detected

For each representative in Figure 4.7(c), the method propose to use region growing as in (Palaiahnakote Shivakumara et al., 2014) for restoring full text lines by referring Sobel edge image of the first frame. As stated in (Palaiahnakote Shivakumara et al., 2014), nearest neighbor criteria is used to determine the angle of orientation of a text line from the candidate text representatives. This uses a candidate text representative belonging to that line as the seed to grow the boundary. The method starts growing

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boundary of the seed point by expanding the boundary, pixel by pixel. For each expanded boundary, the method checks whether the expanded boundary contains white pixel or not. If expanded boundary does not contain white pixel then growing continues until it gets white pixel of nearest neighbor component in the text line. This process continues along the text edge information in the Sobel edge map from the seed representative till it satisfies some convergent criteria. This boundary growing uses converging criteria based on angle information, which allows the proposed method to grow as direction of text line without covering the background information and touching adjacent text lines.

The process of boundary growing is shown in Figure 4.9 where (a) shows initial boundary fixing for each representative, (b) shows merged character boundaries based on nearest neighbor criterion that has been used to find merge adjacent characters in a text line, (c) shows edges of the growing output and (e) shows final text line detected. More details for region growing for multi-oriented text lines extraction can be found in (Palaiahnakote Shivakumara et al., 2014).

4.3 Experimental Results and Discussion

In order to show the effectiveness of the method, well-known existing methods are being implemented that are Mi et al. (Congjie et al., 2005) which use multiple frames for text detection, Huang (X. Huang, 2011) which uses motion vector for detecting text in video and Zhao et al. (Z. Xu et al., 2011) which uses dense corners and optical flow properties for text detection in video. These methods explore the temporal information for text detection, which is same state of art as proposed methods. To evaluate the effectiveness of proposed method over static text, Two methods are also considered for comparison: Liu et al. (C. Liu et al., 2005) and Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010), which do not use temporal information and works for static

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text in single frame of video. Liu et al. proposed a method for text detection in video using texture features and k-means clustering. This method is good for captions text but not for both graphics and scene text. Similarly, Shivakumara et al. proposed improved method which detects both graphics and scene text in video based on the combination of wavelet and color features. However, the method does not work for moving text as scope is limited to text detection in individual frames of video.

4.3.1 Dataset

To evaluate the performance of proposed method, a dataset has been created which includes variety of text from different sources like news channels CNN, CNBC, and NDTV. In total, 250 such videos of 1 to 6 seconds have been considered for evaluating the proposed method out of which 60 videos contain only static text, 100 contains moving text and 90 contains both scene and graphics text together. Few samples from dataset are shown in Figure 4.10. Each video follows 30 frames per second. The reason for collecting dataset videos from the news channels like CNN, CNBC and NDTV's are that they contains variety of moving rolling text with static text present in background. One can also found the variety of font size text in these videos. The observation of the velocity pattern which has been followed throughout this work of moving text can also been observed from such videos. Standard measures proposed in section 3.4.2 is used for evaluation: recall (R), precision (P), f-measure (F) and Average processing time (APT).

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(a) Only scene text

(b) Only graphics text

(c) Both Scene and graphics text

Figure 4.10: Few sample images from datasets

4.3.2 Description of Measures

To evaluate the performance of authors datasets, the same measure Recall (R), Precision (P), F-measure (F) and Average Processing Time (APT) are used as discussed in section 3.4.2. In addition Misdetection Rate (MDR) as defined in (Palaiahnakote Shivakumara et al., 2011) are also considered to evaluate the performance of the method. These categories are defined for each detected block by a text detection method:

- Truly Detected Block (TDB): TDB is a detected block that contains partially or fully text. If the block contains more 80% of the text, it is considered as block with partial text (Palaiahnakote Shivakumara et al., 2011).
- Text Block with Missing Data (MDB): MDB is a detected text block that misses some characters. If the block misses more than 20%, it is considered as missing.

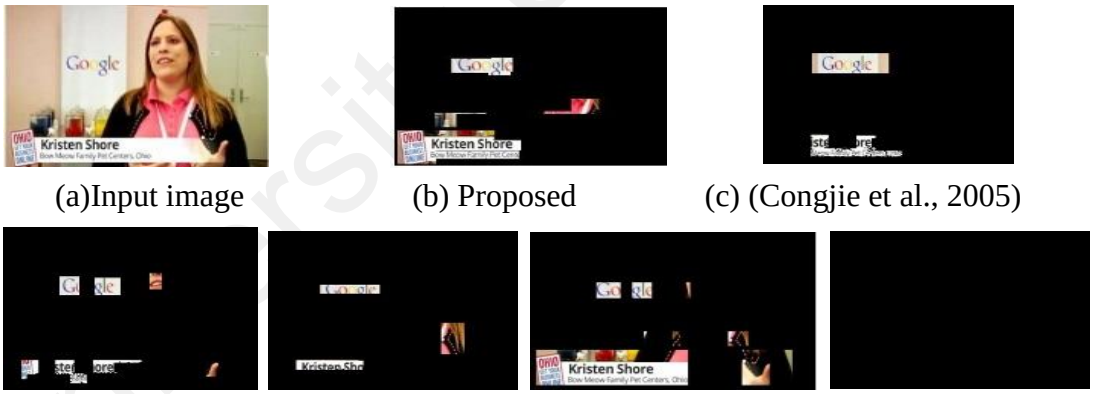
The performance measure is defined as follows:

- Misdetection Rate (MDR) = MDB/TDB,

For authors recorded datasets no ground truth is available that lead us to manually count the measures.

4.3.3 Qualitative and Quantitative Results for static Text

The qualitative results of the proposed and existing methods for static text detection are shown in Figure 4.11. One can see from Figure 4.11 that proposed method detect almost all text with very less false positives while Mi et al. (Congjie et al., 2005), Huang (X. Huang, 2011) and Zhao et al. (Z. Xu et al., 2011) misses some text. Liu et al. (C. Liu et al., 2005) and Shivakumara et al. (Palaiahnakote Shivakumara et al., 2010) misses low contrast texts because both the methods demand high contrast from texture features. The quantitative results of the proposed and existing methods for static text are reported in Table 4.1 where the proposed method is better than existing methods including processing time.



(a)Input image (b) Proposed (c) (Congjie et al., 2005)

(d)(X. Huang, 2011) (e)(Z. Xu et al., 2011) (f) (C. Liu et al., 2005) (g) (Palaiahnakote Shivakumara et al., 2010)

Figure 4.11: Sample result of the proposed and existing methods for static text

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Table 4.1: Performance of the proposed and existing methods for static text

Methods	*R*	*P*	*F*	*MDR*	*APT(Seconds)*
Proposed Method	0.84	0.86	0.85	0.13	1.6
(Congjie et al., 2005)	0.82	0.81	0.81	0.4	2.2
(X. Huang, 2011)	0.78	0.77	0.77	0.3	3.6
(Z. Xu et al., 2011)	0.78	0.79	0.78	0.38	2.8
(C. Liu et al., 2005)	0.76	0.72	0.73	0.18	5.2
(Palaiahnakote Shivakumara et al., 2010)	0.73	0.87	0.77	0.46	42.1

4.3.4 Qualitative and Quantitative Results for dynamic Text

The qualitative results of the proposed and existing methods for dynamic text detection are shown in Figure 4.12 where for the first and the second input frames, most of existing methods fail to detect text properly and for the third frame, most of the methods detect text correctly including the proposed method. On the other hand, the proposed method detects almost all text in all three input frames since it works for both static and dynamic text without any constraints as in the exiting methods. The proposed method finds the text region which has same movement through multiple frames, which includes the static text whose motion is same (near to 0) that makes it detectable by the proposed method. The comparative result is shown in Table 4.2, which shows the performance of all methods for dynamic text.

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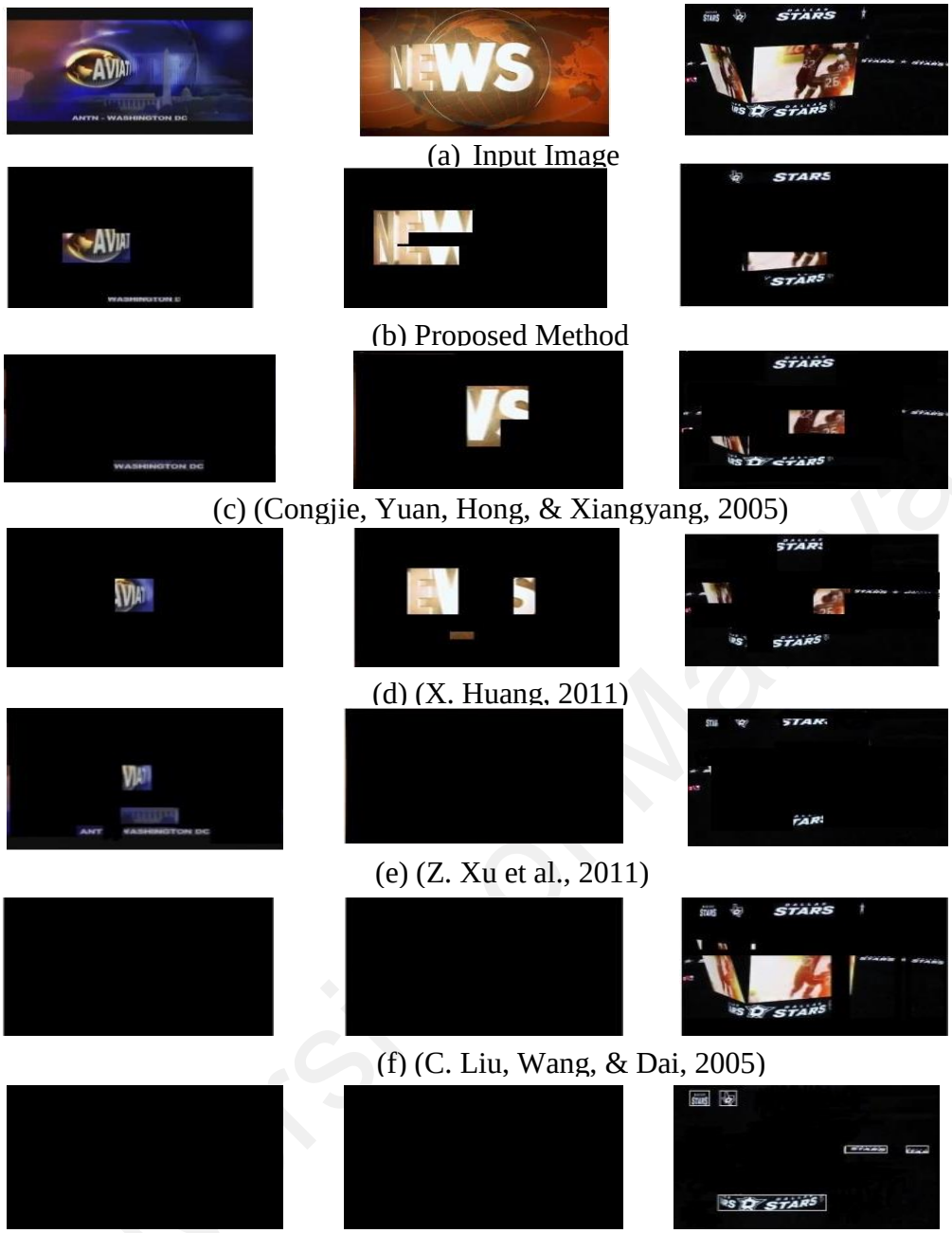

(a) Input Image

(b) Proposed Method

(c) (Congjie, Yuan, Hong, & Xiangyang, 2005)

(d) (X. Huang, 2011)

(e) (Z. Xu et al., 2011)

(f) (C. Liu, Wang, & Dai, 2005)

(g) (Palaiahnakote Shivakumara et al., 2010)

Figure 4.12: Sample results of proposed and existing methods for multi-oriented moving text videos

Table 4.2: Performance of the proposed and existing methods for dynamic text

Method	R	P	F	MDR	APT (Seconds)
Proposed Method	0.89	0.83	0.85	0.13	1.76
(Congjie et al., 2005)	0.66	0.68	0.66	0.42	2.22
(X. Huang, 2011)	0.78	0.79	0.79	0.28	3.3
(Z. Xu et al., 2011)	0.76	0.7	0.73	0.25	2.71
(C. Liu et al., 2005)	0.59	0.60	0.58	0.40	5.38
(Palaiahnakote Shivakumara et al., 2010)	0.66	0.84	0.71	0.52	42.35

4.3.5 Discussion

The key reason behind this response is (Congjie et al., 2005), (X. Huang, 2011) and (Z. Xu et al., 2011) works only for horizontal moving text. Here situations represented contain both static and dynamic text combinations. Existing method are not able to detect the both. On the other hand (C. Liu et al., 2005) and (Palaiahnakote Shivakumara et al., 2010) do not work for moving text which results in there low performance. When the results of Table 4.1 and Table 4.2 are compared, accuracy of the proposed method is almost similar. Therefore, it can be concluded that the proposed method is superior to existing methods in terms of recall, precision, F-measure, misdetection rate and processing time. When this work is compared with the work presented in Chapter 3, the key difference lies in utilizing the temporal information for detecting text candidates. Here the proposed method exploits more information present in temporal information. For the case where frames contain too low contrast text, complex background, the method fails to detect text properly as shown in Figure 4.13 where the proposed method does not detect full text lines and it detects non-text region as a text region. The reason is that moments features for tracing text blocks in temporal frames find mismatch when there is complex background. Therefore, there is a scope for the improvement in future.

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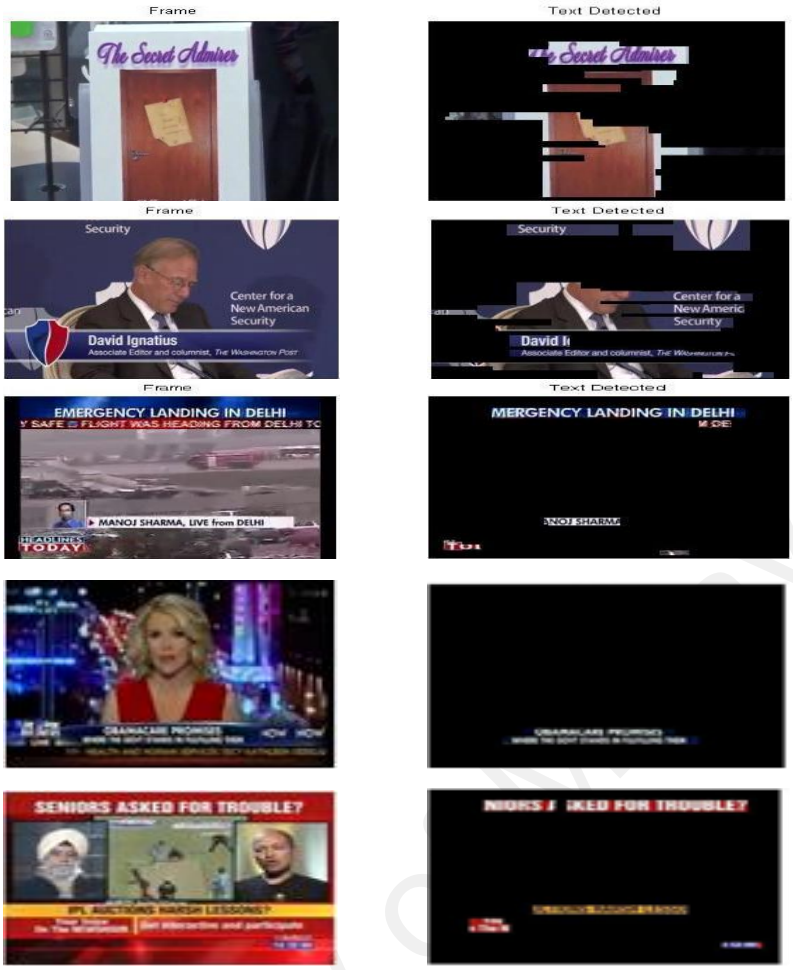

(a). Input frames (b) Text detection results

Figure 4.13: Limitations of the proposed method

Based on the experimental results on authors dataset it can be concluded that the method performs better to detect moving text compare to existing methods. However, there are some limitations discussed in section 4.4.3. The performance of the proposed method may degrade when a video contains low contrast text with complex background.

4.4 Summary

This work presented a novel method for multi oriented moving text detection of both scene and graphics text present in video based on motion vector estimation at block level. The moments are explored for finding the possible text blocks in temporal frames. Gradient directions of text pixels are explored to refine text candidates and

finally region growing is used based on nearest neighbor criterion for restoring text line information regardless of orientation, scripts. However, the proposed method explores inter-frame temporal information between every frame for selecting text that is an improvement from Chapter 3 work but also has a limitation of using only few frames. In addition usage of fixed window size for estimating motion limits the performance of proposed method for multi sized font text, which will be the next consideration for improvement.

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CHAPTER 5: ARBITRARILY-ORIENTED MULTI-LINGUAL TEXT DETECTION IN VIDEOS

It has seen in the previous chapter that usage of fixed window size can reduce the performance of the method. Considering that point in mind, this work will focus on introducing a novel idea for determining automatic window to extract moments for tackling multi-fonts, multi-font size text in the video. In addition another lacking factor in previous proposed method was lying on one question that is "How many frames should one consider for the usage of temporal information that would be enough for correct text detection?" In this work, the temporal information is explored in such a way with developed condition which is capable to choose number of frames automatically and stops when converging criteria meets.

5.1 Introduction

Inspired by the work presented in (H. Li et al., 2000) for multi-oriented text detection in video using the combination of wavelet and moments, where it is shown that moments helps in detecting text candidates for text successfully, the method propose to explore moments in a new way without wavelet support for classifying static and dynamic text clusters using temporal frames. It is noted that (Epshtein et al., 2010; Yang, Quehl, & Sack, 2014) stroke width distance is almost same for the characters in the video, The proposed method utilize the same stroke width distance for determining window size automatically to make the method invariant to different fonts, font size etc. Most of the existing methods which use temporal frames utilize fix number of frames based on pre-defined experiments because the intention of the methods is to use temporal frames for enhancing low contrast text information. Therefore, this work proposes a new iterative procedure that estimates the deviation between first and successive temporal with moments based on the fact (X. Huang, Ma, Ling, & Gao,

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2014) that caption text stay at the same location for few frames while scene text has little movement from one frame to another for separating caption text from scene and background pixels. The advantage of this iterative procedure is that it helps in identifying exact number of temporal frames to be used for text candidate detection. As motivated by boundary growing proposed in (Palaiahnakote Shivakumara et al., 2014) for multi-oriented text detection in video, this method proposes boundary growing without angle projection for arbitrarily-oriented text extraction in video.

5.2 Proposed Method

As discussed in the previous section, moments helps in extracting vital clues of text pixels, such as regular spacing between text pixels and uniform color of the text pixels (Palaiahnakote Shivakumara et al., 2014), the proposed method explore the moments to estimate deviation between temporal frames to separate caption (pixels which stay at the same location) from scene text (pixels which has little movements along background) and background pixels. To obtain such clues for classification, window should be defined for estimating moments. Since video contains multi-font, multi-size text, fixing particular window does not yield good accuracy results. Therefore, the proposed method offers a new idea for determining window automatically based on stroke width information of Sobel and Canny edge images of the input video frame. The proposed method introduces iterative procedure for estimating deviation using moments of pixels in consecutive frames with the help of k-means clustering, which results in static and dynamic text clusters containing caption text and scene text, respectively. The output of clustering is named as text candidates of caption and scene texts in respective clusters. Due to low resolution and complex background, the clustering may misclassify non-text pixels as text pixels. Therefore, gradient direction of text candidates is analyzed to identify the potential text candidates. Furthermore,

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boundary growing is proposed for each potential text candidate to extract full text line of any direction in video. The flow of the proposed method can be seen in Figure 5.1.

It is true that generally, video contains both static and dynamic text. Most of the time caption text refers static text as it stays at same location for few frames since in order to be readable. The proposed method explores the same observations for estimating deviation between the first frame and the successive frames using Euclidean distance. For estimating deviation, moments are proposed for each window (dynamic) in non-overlapping fashion with k-means clustering.

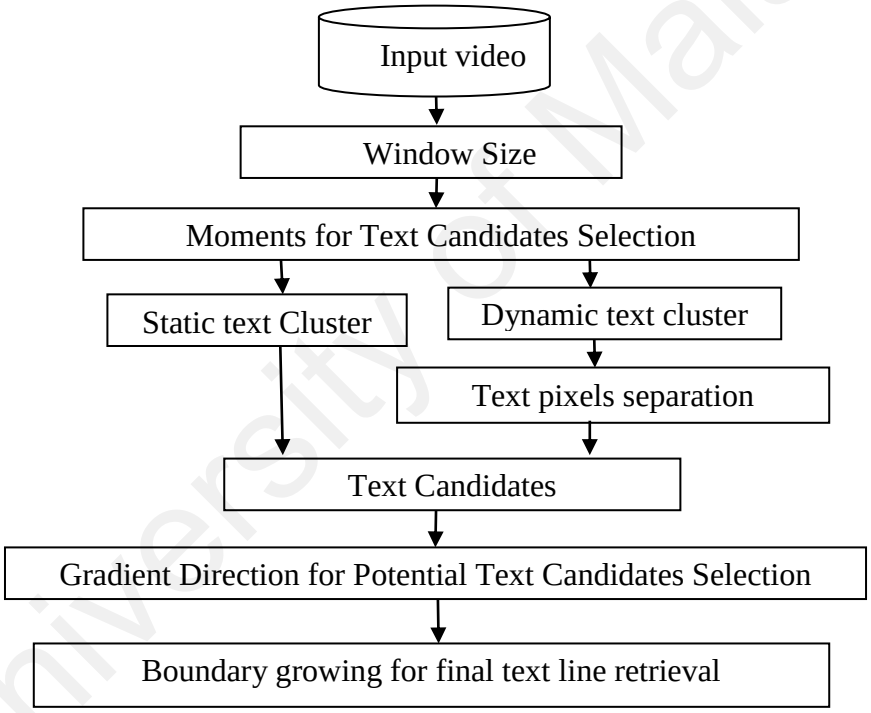

Figure 5.1: Overall framework of the proposed method

5.2.1 Automatic Window Size Detection

It is known that usually, window size is determined based on performance of the method on sample data by varying different sizes, which generally results in study of optimal stroke thickness of text components in images for text detection/recognition. As a result, this procedure may hamper the performance of the method when input data

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contains multi-font and multi-text size as in video. Therefore, this work proposes a new idea for finding window automatically based on stroke width and opposite direction pair. Motivated by the work in (Phan, Shivakumara, & Tan, 2012) for text detection in natural scene images where it is shown that the pattern of text in Sobel and Canny edge images of the input image share the same symmetry property to identify text candidates, so the proposed method find common pixels in Sobel and Canny edge image of the input image, which satisfies stroke width distance and opposite direction pair to identify the common pixels, as defined in equation (5.1).

$$\forall P(i,j): CP_{(i,j)} = 1 \quad if\ (SW_{C(i,j)} == SW_{S(i,j)}) \,\&\&\, (GD_{(i,j)} == -GD_{(i,j+n)}) \tag{5.1}$$

Where for all pixels *(i, j)* of image *P*, a common pixels image *CP* is generated if stroke width for that pixels in canny image SW_C matches with the stroke width in Sobel image SW_S of input. As well as the Gradient Direction (GD) will also be present in opposite pair combination, stating for GVF at location *(i, j)* there will exist an opposite (-GD) at location *(i, j+n).* Here *n* denotes pixels that represent stroke width.

On the common pixels, the proposed method perform histogram operation for stroke width distance vs. frequencies to choose the distance which gives highest peak and the corresponding stroke width distance is considered as window size for moments estimation, which results in candidate text pixel image. It is illustrated in Figure 5.2 where (a) is the input image, (b) is the Sobel edge image, (c) is the Canny edge image, (d) is the common pixels which satisfy the stroke width distance and opposite direction pair in Sobel and Canny edge image and (e) is the histogram where stroke width distance greater than equal to two to choose highest peak are plotted. Note: Pixels that have stroke width distance less than two do not contribute to represent text. It is noticed from Figure 5.2(e) that the stroke width (SW) distance, 2 gives highest peak and hence

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it is considered as window dimension for given input image. The pixels which contribute to highest peak are called candidate text pixels as shown in Figure 5.2(f) where one can see that a few non-text pixels are removed compared to the results in Figure 5.2(d) and text pixels are retained. For the image shown in Figure 5.2(a), 2×2 dimension is considered as actual window dimension. In this way, automatic window size detection helps in retaining strokes that represents text in the video frame without losing significant information. However, Figure 5.2(f) shows that this step misclassifies non-text pixels as candidate text pixels due to complex background and low resolution of video. In addition, it can be seen in Figure 5.2(f) that few text pixels are also lost compared to Figure 5.2(d). This loss does not affect much for the text detection in this work because the restoration steps which will be presented in subsequent sections, restores missing text pixels from the edge image while extracting text lines in the video frame. The main advantage of this step is that the step gives candidate text pixels regardless of caption and scene text type as shown in Figure 5.2(f) where one can see candidate text pixels for caption (bottom line in Figure 5.2(a)) and scene text ("Oreilly" in middle of the image in Figure 5.2(a)). Hence, this step solves two problems: window size detection and candidate text pixels identification by reducing non-text pixels. The candidate text pixels are input for identifying text candidates which will be presented in next Section.

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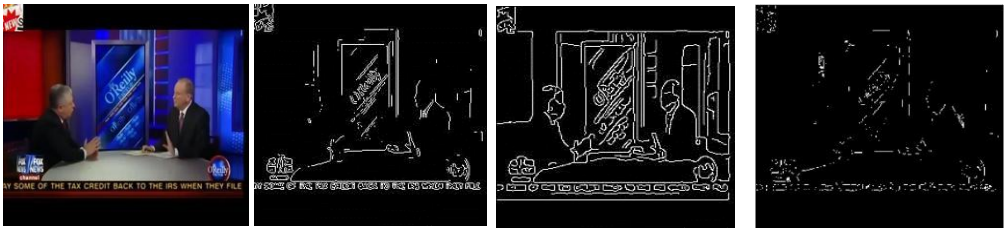
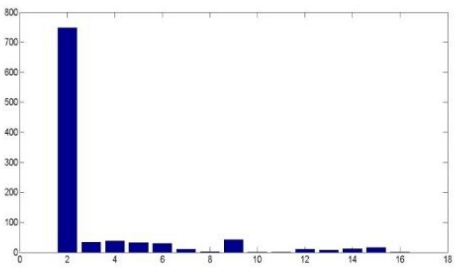


(a) First frame (b) Sobel edge (c) Canny edge (d) Common pixels



(e) Histogram for SW>=2: SW vs. frequencies (f) Candidate pixels of highest peak

Figure 5.2: Automatic window size detection using stroke width (SW) distance and opposite direction pair

5.2.2 Static and Dynamic Text Cluster Classification

It is observed from Figure 5.2(f) that the step presented in Section 3.1 misclassifies non-text pixels as candidate text pixels due to complexity of the problem. In order to classify text pixels accurately, the proposed method proposes to explore temporal information for classifying text and non-text pixels in this Section. As mentioned in (X. Huang et al., 2014), pixel that represents caption text stay at the same location for few frames while pixel that represents scene text (background) have little movements, the proposed method uses the same basis for classifying caption and scene text pixels. Since caption text pixels do not have movements and scene and background pixels have movements, the deviation between caption text pixels is lower than the scene and background pixels. To extract such observation, moment estimation is proposed for the defined window over the first frame and its successive frames. The intuition behind using moments to find deviation is that it provides spatial coherence of text pixels which usually have clusters. As a result, it gives higher value round text and lower around non-text. It can also increase the gap between caption text and scene text regions. For the deviation computed between first and second frame, next the proposed

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method employ k-means clustering with k=2 to classify caption pixels into one cluster (static) and scene, background pixels into another cluster (dynamic). The cluster which gives lowest mean is considered as static cluster (caption text) and other is considered as dynamic cluster (scene text and background pixels), which is called first iteration result. In the same way, the process continues for first and third temporal frame by considering static cluster as input. In other words, the deviation is computed between the result of first iteration and third frame. Again, the k-means clustering with k=2 is deployed to obtain static and dynamic cluster. As iteration increases, the pixels which represent non-text in static cluster classified into dynamic cluster. When all the pixels which represent non-text in static cluster classified into dynamic cluster after certain iterations, dynamic cluster contains nothing. This is the converging criterion for terminating iterative process. As a result, static cluster gives caption text and dynamic cluster gives scene text along with non-text pixels. The same converging criterion helps in deciding the number of temporal frames unlike existing methods (Weihua Huang et al., 2008; C. Liu et al., 2005; Palaiahnakote Shivakumara et al., 2011; Z. Xu et al., 2011) that assume or fixed the number of temporal frames to be used for text detection. The advantage of this step is that it solves two issues: It separates caption text from scene text and background pixels, at the same time it helps in deciding the number of temporal frames.

For each video sequence, *f, f+1, f+2…fn* as shown in Figure 5.3(a), the proposed method employs an iterative procedure to identify text candidates. Here *n* denotes 30 frames per second. For the first iteration, the method considers the first two consecutive frames, say *f* and *f+1* as shown in Figure 5.3(b). Each frame is divided into equal sized blocks of window size. The automatic window size will be determined by the method presented in Section 5.3.1 in a non-overlapping fashion. For each block in *f* and *f+1* frame, a Higher Order Moments (HM) are computed as follows.

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$$HM_{p,q} = \sum_0^N \sum_0^N (x - \mu_x)^p \left(y - \mu_y\right)^q f(x, y) \tag{5.2}$$

where p, q are order of HM and $f(x, y)$ is the image intensity with the corresponding mean μ; N shows the size of image. Then the moments of each block f and f+1 frame are compared using Euclidean distance by following equation.

$$d(p, q) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{5.3}$$

where $p = (p_1, p_2, ..., p_n)$ and $q = (q_1, q_2, ..., q_n)$ are two points in the Euclidean n-space.

The resultant is deviation matrix between the first two frames as shown below.

$$D^{NXN} = \begin{bmatrix} d(0,0) & \dots & d(0,N) \\ . & & . \\ . & & . \\ . & & . \\ d(N,0) & \dots & d(N,N) \end{bmatrix} \tag{5.4}$$

For the deviation matrix obtained from the frames, f and f+1, the method employs a k-means clustering algorithm to classify the pixels which represent low deviation values as static cluster from high deviation values. As a result, the k-means clustering algorithm gives two clusters: a text cluster containing caption (Static cluster-1) and a dynamic cluster containing the scene text and background pixels (Dynamic cluster-1) as shown in Figure 5.3(c) where one can observe a few non-text pixels misclassified as caption text in static cluster-1. The method counts the number of edge components in both Static cluster-1 and Dynamic cluster-1. For the second iteration, the gray values corresponding to Static cluster-1 are considered for deviation estimation with the f+2 frame (the third consecutive temporal frame) as shown in Figure 5.3(d) where one can

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see gray pixels which represents pixels in Static cluster-1. The deviation is estimated between only gray patches in Static cluster-1 and corresponding gray patches in the *f+2* frame (third frame). As a result of the second iteration, two new clusters will made that are Static cluster-2 and Dynamic cluster-2 as shown in Figure 5.3(e). It is observed that the number of edge components in Dynamic cluster-2 have decreased compared to the number of edge components in Dynamic cluster-1. This iterative process continues until the condition satisfies the criterion in which the number of edge components in the Dynamic cluster approaches zero. This is valid because as the iterations increases the number of non-text pixels from Dynamic cluster becomes zero as shown in Figure 5.3(f) where the final Static cluster contains caption text pixels and the final Dynamic cluster contains zero edge components after sixth iteration. To validate this converging criterion, a cumulative graph for the number edge component in Dynamic clusters is shown in Figure 5.4 by adding the number of the edge components of the current iteration to the number of the number of edge components of the previous iteration. It can be observed that the number of edge components increases gradually and remains constant as iteration increases.

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(a) Input: Video sequence starting from *f, f+1, f+2.....fn*

(b) *f* and *f+1* frames as input for the first iteration

(c) Static cluster-1 and Dynamic cluster-1 for the first iteration

(d) Static cluster-1 and *f+2* frame as input for the second iteration

(e) Static cluster-2 and Dynamic cluster-2 for the second iteration

(f) Final, Static cluster-6 and Dynamic cluster-6 at the 6th iteration

Figure 5.3: Iterative process for separating caption pixels from scene and background pixels.

The iteration at which the Dynamic cluster has no edge component, the proposed method considers that the iterative process has met the converging criterion. For the example shown in Figure 5.3, the iterative process terminates at the sixth iteration as shown in Figure 5.4. Since this step considers the output (candidate text pixels) of the step presented in Section 5.3.1, the iterative process terminates quickly and accurately. Therefore, it does not require much processing time for separating caption text from scene and background pixels.

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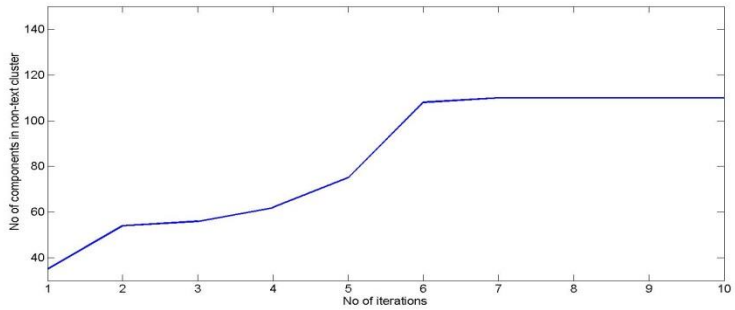

Figure 5.4: Cumulative graph of number of components in non-text cluster for different iteration

It is seen from Figure 5.3(f) that the iterative procedure separates caption text from scene and background pixels successfully. Next, the question is how to separate scene text from the results of Dynamic cluster which contains both scene text and background pixels. Therefore, the proposed method consider compliment of caption text results given by iterative procedure by referring candidate text pixels results given by step presented in Section 5.3.1. This result in scene text pixel with background pixels without caption text pixels as shown in Fig. 5.5(a) where it can be seen can see scene text pixels along with the background pixels. In order to separate scene text pixel from Figure 5.5(a), the proposed method calculates moments as discussed in the above for the pixels in Figure 5.5(a). It is known that text pixels have high contrast compared to its background (Qixiang Ye & Doermann, 2015). As a result, moments give high values for text pixels and low values non-text pixels. Since moments calculation provide gap between text and non-text pixels, the proposed method employ the k-means clustering with k=2 on moments matrix which gives two clusters. The cluster that gives highest mean is considered as text cluster and other one as non-text cluster as shown in Figure 5.5(b) where it can be seen that non-text pixels are removed. Furthermore, the proposed method combines caption text (Figure 5.5(c)) and text cluster (Figure 5.5(b)) by union operation as shown in Figure 5.5(d) where one can see both caption and scene text pixels, which is called text candidates.

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(a) Result of compliment (scene text)

(b) Text cluster by k-means

(c) Caption text by iterative procedure

(d) Union of (b) and (c)

Figure 5.5: Text candidates of caption and scene texts.

5.2.3 Potential Text Candidates Detection for Text Detection

Since considered problem is complex, it is difficult to eliminate false text candidates completely for every input video. For example, the results shown in Figure 5.5(d) suffer from false text candidates and loss of information. To eliminate such false text candidates, the proposed method proposes to explore gradient direction of the text candidate pixels. It is noted from (Palaiahnakote Shivakumara, Phan, Lu, & Tan, 2013) that for character components in text line, most of the gradient direction (GD) of pixels show inward direction and few pixels shows outward direction. Inward direction is defined as the direction which shows towards character. Outward direction is defined as the direction which shows towards nearest neighbor character. Due to influence of nearest neighbor character, few pixels of text candidates show direction away from the text candidates. Based on this observation, the proposed method formulate a rule as if the text candidate is actual text candidate then it must have more number of inward direction (ID) compared to outward directions (OD) else the text candidate is considered as non-text candidate as defined in equation (5). One such example is shown in Figure 5.6, where more number of pixels of character in Figure 5.6(a) show inward directions (green arrows) compared to outward directions (red arrows) and

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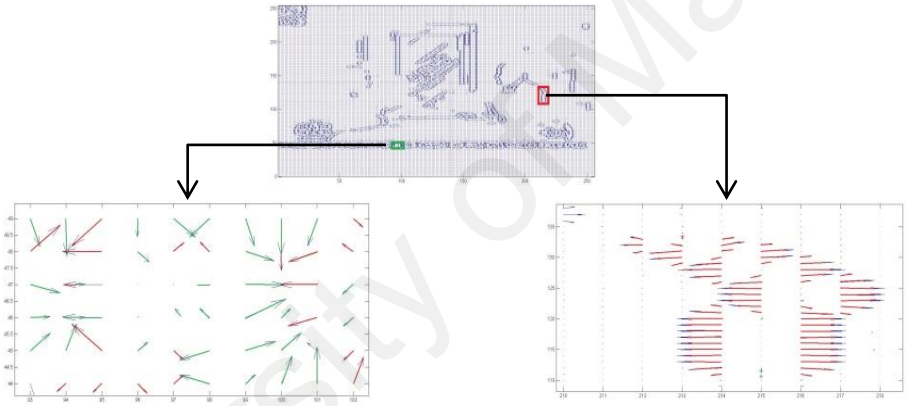
pixels of non-text component in Figure 5.6(b) does not satisfy this formulation. In addition, it is observed from Figure 5.6(b) that the directions of candidate pixels are arbitrary due to background influence. The effect of this formulation can be noticed in Figure 5.6(c) and Figure 5.6(d) where Figure 5.6(c) is the final result which combines (union) of caption and scene text shown in Figure 5.5(d), and Figure 5.6(d) does not have any false text candidates. Therefore, the output of this step is called potential text candidates (PTC) that can be defined as:

$$PTC = \begin{cases} ID(GD_i) > OD(GD_{(i)}) & : Text \\ Otherwise & : Non-text \end{cases} \quad (5.5)$$



(a) Text components (b) Non-text component

(c) Union of caption and scene text (d) Effect of inwards and outward directions

Figure 5.6: Potential text candidates from union of caption and scene text pixels

One can notice from Figure 5.6 (d) that image contain loss of text information because the above formulation and clustering presented in Section 5.3.2 may eliminate significant text pixels sometimes. To restore full text lines using potential text

candidates, the proposed method proposes boundary growing which extracts edge components from Sobel edge image of the input frame corresponding to potential text candidates in Figure 5.6(d) as shown in Figure 5.7(a) where edge components for corresponding potential text candidates can be seen, in Figure 5.6(d). Next, the boundary growing method fixes bounding boxes for the edge component as shown in Figure 5.7(b) where rectangular boxes are shown. It expands boundary towards outward gradient direction of pixel of the edge component pixel by pixel in Sobel edge image of the input frame until it reaches nearest neighbor components based on nearest neighbor criterion as shown in Figure 5.7(c)-(f) where boundary of the potential candidates are expanded until it finds nearest neighbor component. This process continues till it reaches end of the text line as shown in Figure 5.7(g) where it can be seen full text line is covered. Finally, the boundary growing method extracts text from the input frame corresponding to the results in Figure 5.7(g) as shown in Figure 5.7(h) where it is seen full text lines of both caption and scene text. This growing works well because of the fact that the space between the characters is lesser than the space between words and the text lines as it is stated in (Palaiahnakote Shivakumara et al., 2014).

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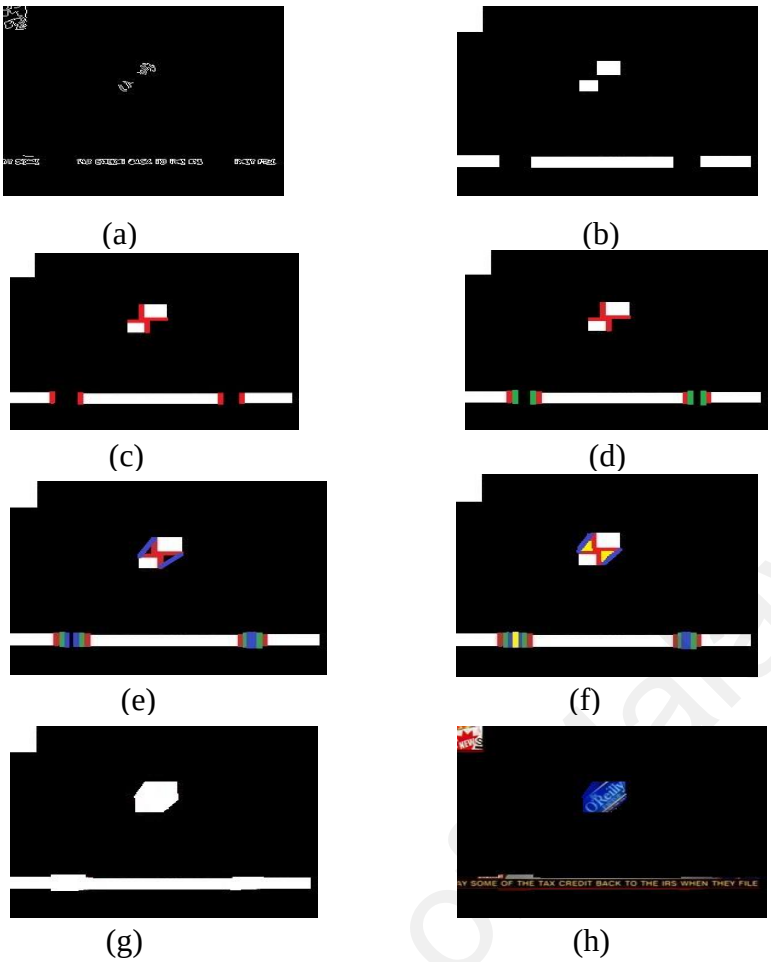

Figure 5.7: Boundary Growing to detect full multi-oriented text lines: (a) Restored edge components from Sobel edge image of the input frame corresponding to potential text candidates, (b) Boundary fixing for edge components, (c)-(g) intermediate results of boundary growing towards outward direction of pixels of edge components, (g) is final growing results and (h) is text extraction results.

5.3 Experimental Results and Discussion

In order to show superiority to existing methods, state-of-the-art methods of different categories are implemented, such as the methods of natural scene images, video with temporal and without temporal frames, video with horizontal text and non-horizontal texts, etc. For example, the work in (Epshtein et al., 2010), which is the state-of-the-art method, proposes a stroke width transform for text detection in natural scene images, and it is considered as a benchmark method. Liu et al. (C. Liu et al., 2005) proposed texture features for text detection in both video and natural scene images. Shivakumara et al. (P. Shivakumara et al., 2010) used the combination of

Fourier and color for detecting text in both images and video without temporal information. Shivakumara et al. (Palaiahnakote Shivakumara et al., 2012) explored a Bayesian classifier for text detection in video without temporal information. Khare et al. (Khare et al., 2015) used a HOM descriptor for detecting text in video using temporal information. Yin et al. (X.-C. Yin et al., 2014) used Maximally Stable Extremal Regions (MSERs) as character candidates and the strategy of minimizing regularized variations for text detection in natural scene images. It is robust to multi-orientations, multi-fonts and multi-size text. Mi et al. (Congjie et al., 2005) used multiple frames for text detection with temporal frames. Huang, (X. Huang, 2011) used motion vectors for detecting text in video with temporal information. Zhao et al. (Z. Xu et al., 2011) used dense corners and optical flow properties for text detection in video with temporal information. Note: For the methods which do not use temporal frames, such as natural scene text detection methods and a few video text detection methods, key frames are extracted from each video to give inputs for the methods. And for tracking results on ICDAR 2015 video data, word is detected over individual frame by the text detection methods and added to track system to track the text as per instructions in (Karatzas et al., 2015).

5.3.1 Datasets

To evaluate the performance of the proposed method, experiments are conducted on standard datasets, namely, ICDAR 2013 (Karatzas et al., 2013), YVT (Nguyen, Wang, & Belongie, 2014), ICDAR 2015 (Karatzas et al., 2015) videos. Author's dataset of 100 video of 1 to 6 seconds is also created that contains arbitrary-oriented any multi-script text. This dataset has been created to test the proposed method multi-lingual text detection ability because there is no standard dataset available publicly and the above mentioned standard datasets do not contain much different script text lines. ICDAR 2013 and ICDAR 2015 video usually contain lots variations in fonts, contrast, font

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sizes and background variations. YVT data contains only scene text that includes variety of background, such as building, greenery, sky etc. Author's data includes arbitrarily oriented text lines of different scripts with background variations. In summary, all datasets are collected to test the generic property of the proposed method.

5.3.2 Description Measures

The proposed method uses standard measures proposed in (Karatzas et al., 2013) and discussed in section 3.4.2 for calculating recall (R), precision (P) and f-measure (F) for ICDAR 2013 and YVT video datasets, while for ICDAR 2015 video data the proposed method uses the measures used in (Karatzas et al., 2015) where it suggests the same formula as in (Karatzas et al., 2013) discussed in section 3.4.2 of this thesis. In addition to this tracking measures are also considered. The definitions are as follows. Multiple Object Tracking Precision (MOTP), which expresses how well locations of words are estimated, and the Multiple Object Tracking Accuracy (MOTA), which shows how many mistakes the tracker system made in terms of false negatives, false positives, and ID mismatches. On the other hand, the Average Tracking Accuracy (ATA) provides a spatio-temporal measure that penalizes fragmentations while accounting for the number of words correctly detected and tracked, false negatives, and false positives.

Given a video sequence an ideal text tracking method should be able to detect all text words present at every frame and estimate their bounding boxes precisely; additionally it should also keep consistent track of each word over time, by assigning a unique ID which stays constant throughout the sequence (even after temporary occlusion, etc). For every time frame t a text tracking system outputs a set of hypotheses $\{h_1^t,.....,h_n^t\}$ for a set of words in the ground-truth $\{w_1^t,.....,w_m^t\}$. Those frame level objects can be grouped by their unique identifiers into sequence level

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hypotheses $\{H_1,.....,H_p\}$ and ground-truth words $\{W_1,.....W_q\}$ (that typically span more than one frame). For a distinctive notation it is referred as H_i^t and W_i^t to the frame level objects at frame *t* in H_i and W_i respectively.

The evaluation procedure is based on a mapping list of word-hypothesis correspondences. At the frame level it has a mapping M_t for each frame *t* in the video sequence made up with the set of pairs (w_i^t, h_j^t) for which the sum of overlap (w_i^t, h_j^t) is maximized, where overlap $(\cdot)$ is a function overlap $(w_i^t, h_j^t) = \frac{a(w_i^t \cap h_j^t)}{a(w_i^t \cup h_j^t)}$ of the intersection area $(a(\cdot))$ of their bounding boxes. Additionally, a pair (w_i^t, h_j^t) is considered a valid correspondence iff overlap $(w_i^t, h_j^t) > 0.5$. At the sequence level it has a unique mapping M of word hypothesis correspondences (W_i, H_j) combinations.

The two CLEAR-MOT metrics are calculated using the frame level mappings as:

$$MOTP = \frac{\sum_{i,t} o_t^i}{\sum_t c_t} \tag{5.6}$$

where o_t^i refers to the overlapping ratio of the *i*th correspondence in the mapping M_t and c_t is the number of correspondences in M_t; and:

$$MOTA = 1 - \frac{\sum_t (fn_t + fp_t + id\_sw_t)}{\sum_t g_t} \tag{5.7}$$

Where fn_t, fp_t, id_sw_t, and g_t refer respectively to the number of false negatives, false positives, ID switches, and ground-truth words at frame *t*. The Sequence Track

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Detection Accuracy (STDA) is calculated by means of the sequence level mapping M as:

$$STDA = \sum_{i=1}^{N_M} \frac{\sum_t m(W_i^t, H_i^t)}{N_{W_i \cup H_{i \neq \phi}}} \tag{5.8}$$

Where N_M is the number of correspondences in M, $N_{W_i \cup H_{i \neq \phi}}$ is the number of frames where either W_i or H_i exist, and $m(W_i^t, H_i^t)$ takes a value of 1 iff overlap $(W_i^t, H_i^t) > 0.5$ or 0 otherwise. The STDA is a measure of the tracking performance over all of the objects in the sequence and thus can take a maximum value of N_W, which is the number of ground-truth words in the sequence. The Average Tracking Accuracy (ATA), which is the normalized STDA per object, is defined as:

$$ATA = \frac{STDA}{\left\lfloor \frac{N_w + N_H}{2} \right\rfloor}$$

More information can be found in (Karatzas et al., 2015). For authors data, same definitions as in (Karatzas et al., 2013) is used at line level but not word level. The main reason to calculate measures at line level is that fixing bounding box for the word of arbitrarily-oriented text is hard. Besides, for different script text lines, spacing between the words is not consistent as in English to segment words accurately. Therefore, recall, precision and f-measure are calculated for the lines as it is common practice for video text detection (Qixiang Ye & Doermann, 2015). Since the ground truth is available for all standard data, ICDAR 2015, ICDAR 2013 and YVT video data at word level, the proposed method use the same ground truth for calculating measures and for authors datasets measures are calculated at human level.

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5.3.3 Analysing the Contributions of Dynamic Window Size and Deviation Steps

The proposed method involves two key steps for text detection of arbitrarily-oriented multi-lingual text in video. It proposes a method for finding automatic window based on stroke width distances of the common edge components in Sobel and Canny edge image of the input frame. The same steps also help in identifying candidate text pixels. Another, an iterative procedure for the deviation values to the candidate text pixel for separating caption text from scene and background pixels, which in turn results in text candidates of both caption and scene text, and to determine the number of frames. Therefore, in order to know the effect of each step, the proposed method conduct experiments on different combinations of these two steps by calculating recall, precision and F-measures. For this experiment, the proposed method uses authors dataset which includes English and multi-script text lines of different orientations, as discussed in the above section. The reason for only using authors data is that it is more complex than standard video datasets. The combinations of these two steps are (1) With Automatic Window (AW) and Without Deviation (D). In this step, the proposed method deploys the step of automatic window selection and the proposed method calculates the average of the moments for each sliding window over 10 frames without using an iterative procedure proposed in section 5.3.2. This results in a moment's matrix with the same dimensions of the input frame. Then, it applies k-means clustering with k=2 for identifying text candidates. In other words, for this experiment, the proposed method does not use an iterative procedure by calculating deviation values between the first frame and successive frames. (2) Without Automatic Window and With Deviation, where the proposed method does not use the step of automatic window selection, it fixes an 8×8 window and it uses an iterative procedure for text candidate detection. (3) Without Automatic Window and Without Deviation, where the proposed method does not use both the steps. (4) With Automatic Window and With Deviation,

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where the proposed method uses both the steps for calculation. The effect of these experiments is shown in Fig. 8, where one can notice that for input Figure 5.8(a), with automatic window and with deviation, this gives better results than other combinations as shown in Figure 5.8 (e). If the effect of the other three combinations are compared, without automatic window and with deviation gives better results than with automatic window and without deviation, and without automatic window and without deviation as shown in Figure 5.8 (c). It is observed from Figure 5.8(b)-(e) that with automatic window detects the big font "GIVI" and the same text is missed without the automatic window. In the same way, Figure 5.8 (b)-(e) show that with the use of deviation, it detects almost all text lines other than the big font, while without using the deviation, text lines are missed. Therefore, it can be concluded that the automatic window selection steps helps in detecting multi-fonts and multi-size texts while the iterative procedure for deviation helps in detecting texts without missing any. Overall, these two steps help to improve the performance of the proposed method. Experimental results are reported in Table 5.1 for the different combinations from which same conclusion can be drawn.

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(a) Input frame

(b) With DW and without Deviation

(c) Without DW and with Deviation

(d) Without DW and without Deviation

(e) With DW and with Deviation

Figure 5.8: Sample results for different combinations of automatic window selection and deviation for frames selection. AW denotes Automatic Window and D denote Deviation.

Table 5.1: Performance of the proposed method for different combinations of Automatic Window (AW) and Deviation (D)

Measures	With DW and without Deviation	Without DW and with Deviation	Without DW and without Deviation	With DW and with Deviation
R	55.4	52.7	48.1	65.1
P	57.8	53.8	42.6	66.7
F	56.6	53.2	45.3	65.9

5.3.4 Experiments on Arbitrarily-Oriented English and Multilingual Video

Sample qualitative results of the proposed and the existing methods for authors English and Multi-lingual video are shown in Figure 5.9 and Figure 5.10, respectively. It is noted from Figure 5.9 and Figure 5.10 that the proposed method detects almost all text and it is better than the existing methods. Figure 5.9 includes sample scripts of Telugu which is a south Indian language of Andhra Pradesh state, Bangla which is the language of West Bengal state of India, as well as Chinese and Arabic, respectively. It can be observed from the frames of different scripts that each script has its own structure with different styles, fonts and shapes. This makes the problem more challenging for the method, which does not have the ability to handle multi-lingual

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script text lines compared to English texts. The main cause for getting poor accuracy from the existing methods is that those methods do not have the ability to handle arbitrarily-oriented text and multi-lingual text in video. As a result, the existing methods miss some texts. It is evident from the quantitative results of the proposed and existing methods for English video and Multi-lingual video reported in Table 5.2, the proposed method gives better precision and F-measure compared to existing methods. The methods reported in (Khare et al., 2015; Palaiahnakote Shivakumara et al., 2012; P. Shivakumara et al., 2010; X.-C. Yin et al., 2014) score close to the proposed method's results because these methods are robust to non-horizontal orientations and to the extent of multi-lingual script text lines compared to other methods. Table 5.2 shows that the proposed methods score lower results for Multi-lingual video compared to English video including the proposed method. This shows that text detection in multi-lingual video is difficult compared to English video.

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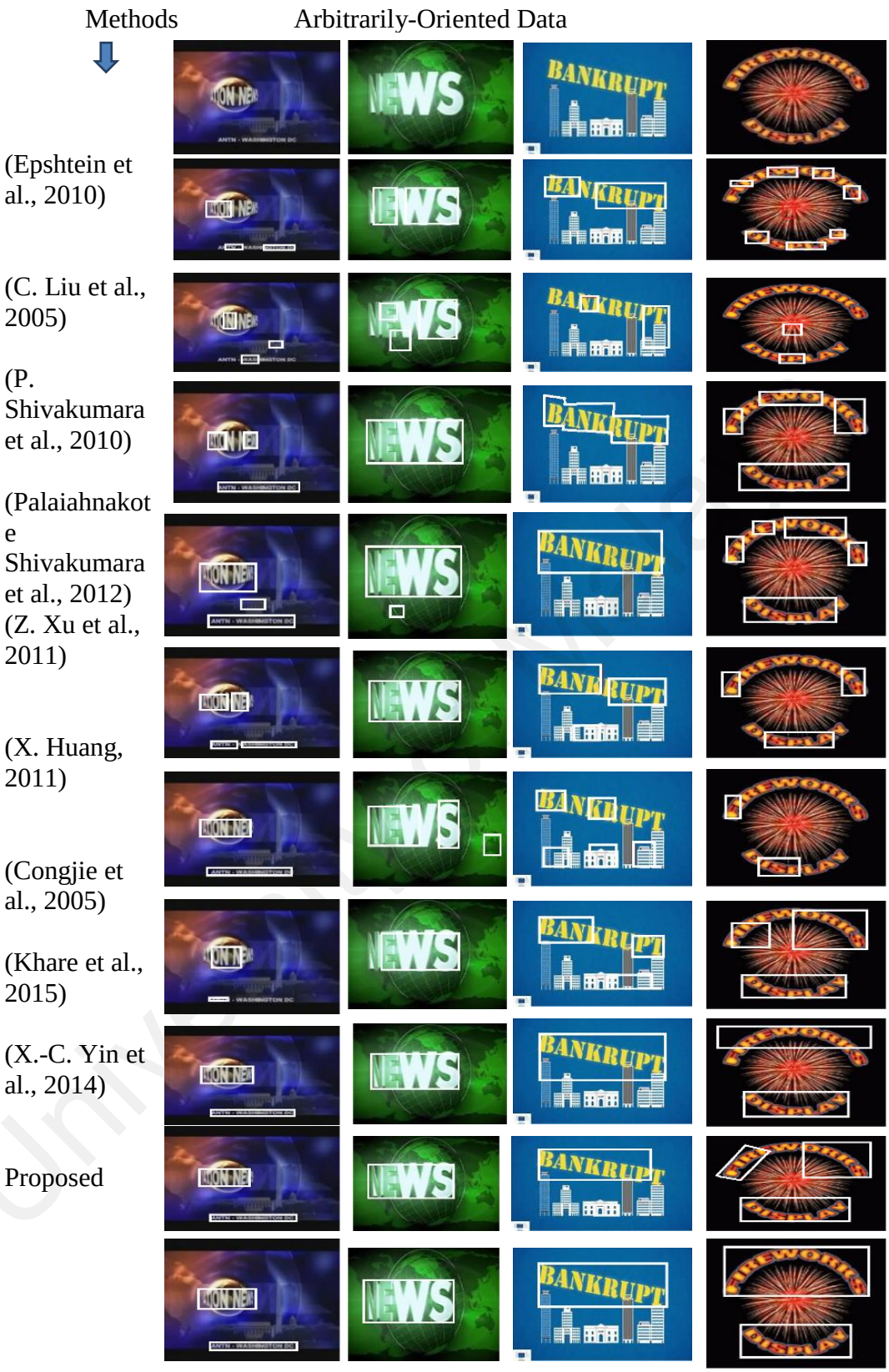

Figure 5.9: Sample results of the proposed and existing methods on an arbitrarily-oriented video dataset

Figure 5.10: Sample results of the proposed and existing methods on Author's multilingual dataset

Table 5.2: Text detection results of the proposed and existing methods for Author's English and Multi-Lingual Video datasets

Methods	Video with English Texts			Multi-Lingual Videos		
	R	P	F	R	P	F
(Epshtein et al., 2010)	58.23	51.17	54.99	20.53	22.9	21.68
(C. Liu et al., 2005)	36.3	34.7	35.48	26.9	23.44	25.1
(P. Shivakumara et al., 2010)	38.12	62.32	47.30	31.2	29.9	30.92
(Palaiahnakote Shivakumara et al., 2012)	65.1	42.62	51.51	35.41	32.5	33.92
(Z. Xu et al., 2011)	61.49	57.3	59.33	32.4	31.52	31.96
(X. Huang, 2011)	49.3	46.9	48.07	33.6	41.7	32.63
(Congjie et al., 2005)	49.1	49.9	49.41	46.4	46.17	46.31
(Khare et al., 2015)	53.9	52.7	53.29	48.4	49.3	48.84
(X.-C. Yin et al., 2014)	52.4	64.3	57.9	54.7	50.31	52.4
Proposed Method	**65.12**	**66.7**	**65.9**	**52.3**	**53.4**	**52.8**

5.3.5 Experiments on Standard ICDAR 2013, YVT and ICDAR 2015 Videos

Sample qualitative results of the proposed and existing methods for ICDAR 2013, YVT and ICDAR 2015 video are shown in Figure 5.11-Figure 5.13, respectively, where it can be noted that the proposed method detects almost all text lines in the video frames. The quantitative result of the proposed and existing methods for ICDAR 2013, YVT and ICDAR 2015 video data are reported in Table 5.3 and Table 5.4, respectively. Table 5.3 shows that the proposed method is better than existing methods for both ICDAR 2013 and YVT video. The reason for poor results of the existing method is that the YVT dataset comprises complex backgrounds while the ICDAR comprise low contrast text with background variations. In addition, the ICDAR datasets contain a few European script text lines but the YVT data contains English and Chinese. Table 5.3 shows that Shivakumara et al. (P. Shivakumara et al., 2010), Yin et al. (X.-C. Yin et al., 2014) and Khare et al. (Khare et al., 2015) score results close to the proposed method's results because these methods are robust to contrast variations and multi-font and text size. Epshtein et al. (Epshtein et al., 2010) developed a method for text detection in natural scene images but not video images. Liu et al. (C. Liu et al., 2005) method is

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sensitive to orientations as it was developed for horizontal direction text images. Shivakumara et al. (Palaiahnakote Shivakumara et al., 2012) requires proper samples to train the Bayesian classifier. The methods described in (Congjie et al., 2005; X. Huang, 2011; Z. Xu et al., 2011) fix the number of temporal frames. On the other hand, the proposed method has the ability to handle multi-font, multi-size texts, arbitrary orientations and multi-scripts, and hence it gives better results compared to existing methods.

For ICDAR 2015 video data, results are reported according to (Karatzas et al., 2015) where measures are calculated based on tracking results. In the same way, results of the proposed and existing methods are reported in Table 5.4. It is noted from Table 5.4 that the proposed method is the best at MOTA while AJOU (Karatzas et al., 2015) is the top performer at MOTP and Deep2Text is the top performer at ATA. Since the proposed method is developed to handle arbitrary-oriented-multi-lingual text, it scores slightly low accuracy for the ICDAR 2015 in terms of MOTP and ATA compared to the best performer in ICDAR 2015 robust competition. On the other hand, since AJOU, Deep2Text methods are developed for ICDAR 2015 video data to track the words in the video, the methods achieves the best results. Since other existing methods are developed for text detection but not tracking the text in video, the methods scores low results compared to the proposed methods and top performers in ICDAR 2015 robust competition.

In summary, the proposed steps in Section 5.3.1 which automatically estimates the window size for identifying candidate text pixels, followed by Section 5.3.2 which identifies static and dynamic text by estimating number of frames to be utilized and then Section 5.3.3 which identifies potential text candidates and detect text line using boundary growing are invariant to rotation, scaling and scripts. Therefore, the objective of the work is achieved.

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Figure 5.11: Sample results of the proposed and existing methods on ICDAR2013 video dataset

Figure 5.12: Sample results of the proposed and existing methods on YVT video dataset

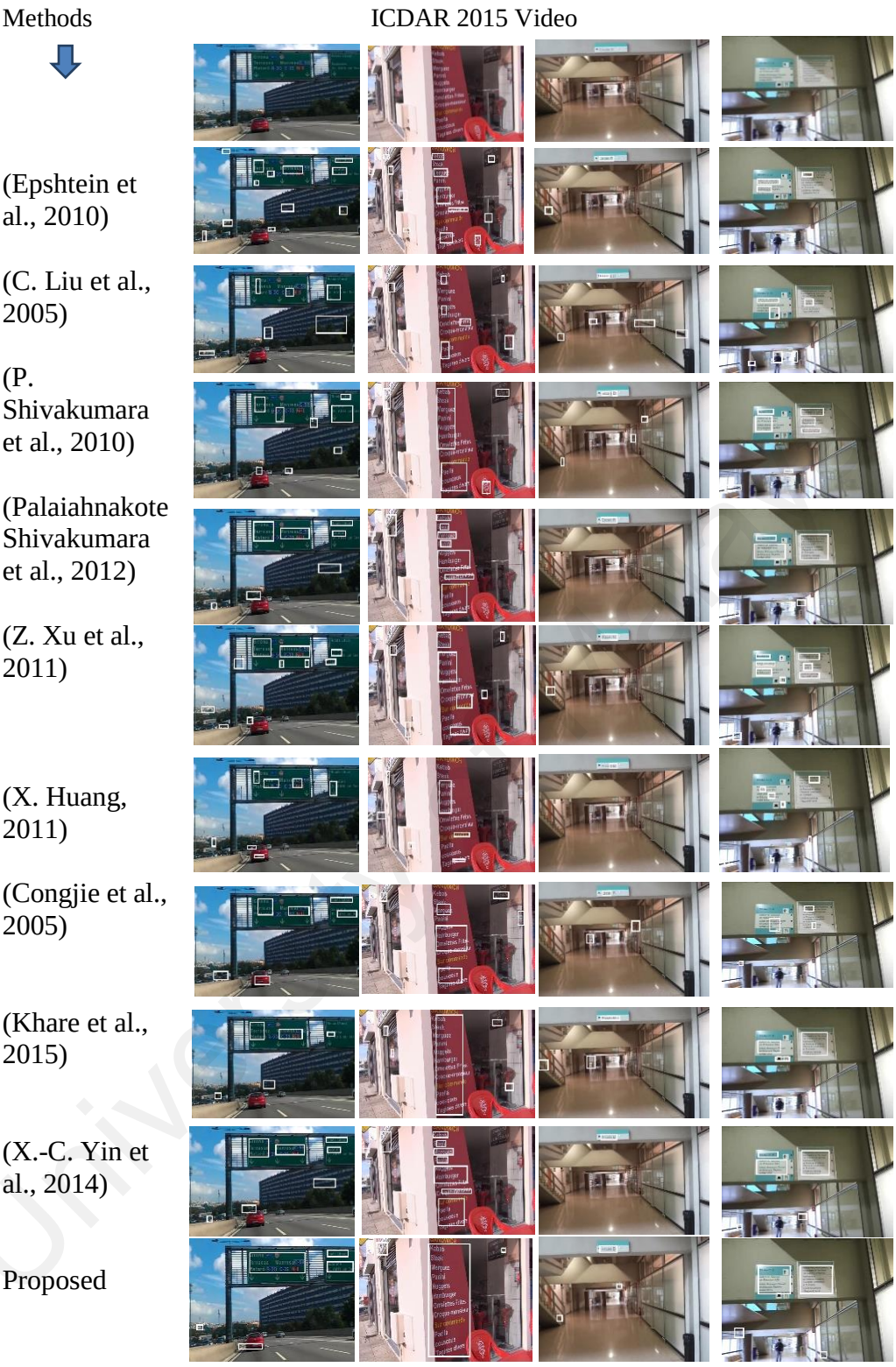

Figure 5.13: Sample results of the proposed and existing methods on ICDAR2015 video dataset

Table 5.3: Text detection results for standard ICDAR 2013 and YVT videos

Methods	ICDAR2013			YVT		
	R	P	F	R	P	F
(Epshtein et al., 2010)	32.53	39.80	35.94	40.56	46.22	43.35
(C. Liu et al., 2005)	38.91	44.60	41.62	33.73	42.35	39.09
(P. Shivakumara et al., 2010)	50.10	51.10	50.59	56.68	54.38	55.43
(Palaiahnakote Shivakumara et al., 2012)	53.71	51.15	50.67	54.53	50.34	52.71
(Z. Xu et al., 2011)	46.30	47.02	46.65	51.6	47.96	49.73
(X. Huang, 2011)	32.35	32.50	32.42	43.73	44.92	44.31
(Congjie et al., 2005)	40.30	26.92	32.76	40.86	38.1	49.84
(Khare et al., 2015)	47.6	41.4	44.3	55.2	52.71	53.93
(X.-C. Yin et al., 2014)	54.73	48.62	51.56	57.35	51.7	54.43
Proposed Method	**55.9**	**57.91**	**51.7**	**57.9**	**52.6**	**55.16**

Table 5.4: Text detection results for standard ICDAR 2015 videos

Methods	ICDAR 2015		
	MOTP	MOTA	ATA
(Epshtein et al., 2010)	43.4	37.75	35.28
(C. Liu et al., 2005)	42.99	36.95	34.8
(P. Shivakumara et al., 2010)	70.22	49.73	39.37
(Palaiahnakote Shivakumara et al., 2012)	71.7	32.3	41.29
(Z. Xu et al., 2011)	64.61	45.93	34.36
(X. Huang, 2011)	44.3	36.62	34.5
(Congjie et al., 2005)	52.86	29.48	32.37
(Khare et al., 2015)	72.46	59.89	40.1
(X.-C. Yin et al., 2014)	73.51	50.47	41.26
AJOU (Karatzas et al., 2015)	**73.25**	53.45	38.77
Deep2Text-I (Karatzas et al., 2015)	71.01	40.77	**45.18**
Proposed Method	73.16	**52.93**	43.02

5.4 Summary

In this work, a new method for arbitrarily-oriented-multi-lingual text detection in video based on moments and gradient directions is proposed. The proposed method introduces a new idea for finding automatic window based on commons stroke width of Sobel and Canny edge images of input frame. The same step helps in identifying candidate text pixels. Then the proposed method explores temporal information for text candidate detection by introducing an iterative procedure based on deviation between consecutive frames along with k-means clustering. It also finds solution to decide the

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number of temporal frames for identifying text candidates. Furthermore, the gradient inward and outward directions of pixels of edge components are used for eliminating false text candidates, which results in potential text candidates. The boundary growing is proposed for potential text candidates to extract full text line using Sobel edge image based on nearest neighbor criterion. Experimental results on different standard datasets show that the proposed method outperforms the existing methods. Besides, the experimental result shows that the proposed method is independent of orientation, scripts, data, and fonts. However, Stroke width information is used here which is required for estimating the window size in this work and it is a known fact that edge and stroke width information degrades in presence of blur and other type of distortion. The performance of the proposed method may get affected in the presence of blurred text which is common in the case of videos.

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CHAPTER 6: A BLIND DECONVOLUTION METHOD FOR TEXT DETECTION AND RECOGNITION

In previous chapter, there is one common problem is that the performance of the methods degrades when video affected by blur. This chapter presents a combine quality metrics for estimating degree of blur in the video/image. Then the proposed method introduces blind deconvoution model, kernel based energy minimization which enhances the edge intensity by suppressing blur pixels.

6.1 Introduction

It is observed from the literature (Cao, Ren, Zuo, Guo, & Foroosh, 2015) on text detection and recognition that distortion due to motion blur is a major issue among all other artifacts because blur interferes with the structure of the components which in turn changes the shape of the components. It is known that usually text detection and recognition methods directly or indirectly use the structure of the components for achieving good results. Therefore, the same methods fail to give satisfactory results when blur exist in the video/image. It is evident from the paper (Palaiahnakote Shivakumara et al., 2015) that blur is the main cause to get poor accuracy of the methods because edge or gradient-based methods are sensitive to blur and distortions. This problem can be solved in two ways: (1) developing a method which can withstand causes given by blur artifact and (2) developing a method for deblurring the blur image to restore the structure of the components. In this work, the second approach is selected because developing a method which is invariant to blur is challenging (Cao et al., 2015). Therefore, it can be asserted that there is a need for developing a method for deblurring the blurred image for improving the performance of the text detection and recognition methods in a real-time environment.

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One such example is illustrated in Figure 6.1 where it can be observed from Figure 6.1 (a) that a text detection method fails to detect text in a blurred image while the same method detects text in a deblurred image. However, for binarization, the text detection methods are manually tuned to detect a full text line in the blurred frame as shown in Figure 6.1(b) to validate the binarization method. Despite the fact that a, full text line is input to the binarization methods, they fail to preserve the shape of the characters in the blurred text, whereas for the text in the deblurred frame, the binarization method preserves the shape of the characters as shown in Figure 6.1(c). Therefore, the same conclusions can be drawn from the results in Figure 6.1 (b)-(d) that Optical Character Recognizer (OCR) gives poor results for blurred text and gives good results for deblurred text. For illustration purposes, as shown in Figure 6.1, the method by Kumar et al. (Kumar et al., 2014) is used for deblurring which explores geometrical moments. For text detection, the method proposed in (P. Shivakumara et al., 2010) is used, which explores the combination of color and Fourier along with boundary growing for both graphics and scene text detection in video. For binarization, Otsu (Otsu, 1975) method is used as it is a popular global thresholding technique. The recognition results are shown in Figure 6.1 obtained by Tesseract OCR which is available publicly (Tesseract).

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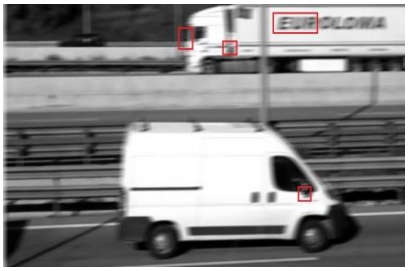


(a) Text detection for a blurred image and a deblurred image by (Kumar et al., 2014)


(b) Text line detected by (P. Shivakumara et al., 2010) the text detection method in (a)


(c) Binarization results for the text line images in (b) by the method (Otsu, 1975)

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(d) Recognition results by OCR (Tesseract) for respective binary text lines in (c)

Figure 6.1: Illustrating text detection and recognition for blurred and deblurred frames

6.2 Proposed Method

Generally, natural scene video consists of a large number of text and non-text frames. While capturing videos, it is obvious that several frames get affected by blur due to the object or camera motion. As a result, text detection and recognition methods may not give successful results. For the proposed work, video or images affected by blur are input to enhance the performance of the text detection and recognition methods. Since the main goal of this work is to improve text detection and recognition methods for blurred images, the proposed method considers the images with uniform blur and thus consider addressing non-uniform blur as beyond the scope of this work. To solve this problem, first system needs to classify the blurred frames from the pool of video frames. The proposed method explores quality assessment metrics in a different way to classify blurred frames from non-blurred frames. The classified blurred frames are passed to the proposed deblurring model to restore fine information such that text detection and recognition methods give successful results. The proposed deblurring model is derived based on Gaussian weighted GW- L1 norm and kernel based energy

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minimization. Furthermore, experiments on text detection and recognition by several methods are provided to show the usefulness and effectiveness of the deblurring model. The flow diagram of the proposed method can be seen in Figure 6.2.

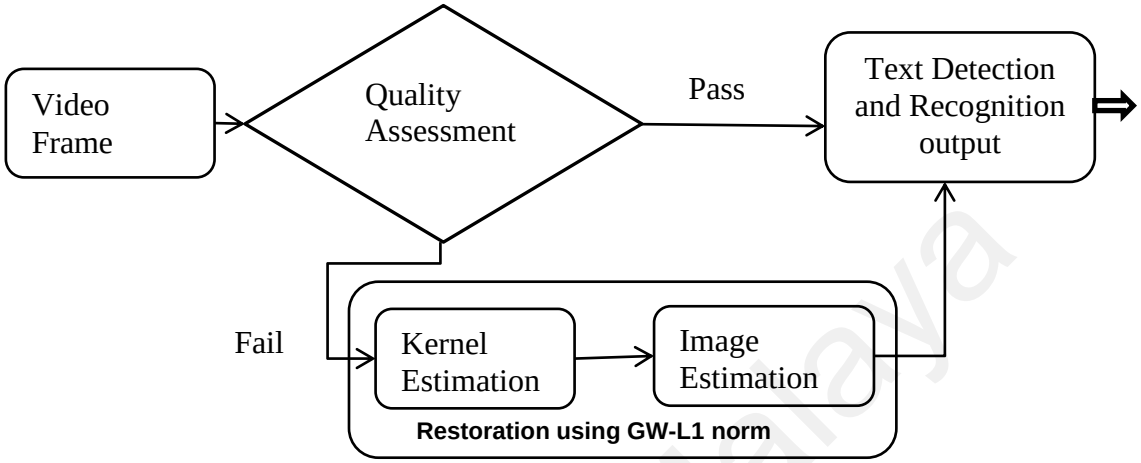

Figure 6.2: Proposed Methodology framework

6.2.1 Classification of Blur and Non-Blur Frame in Video

For the given video or images with blur artifacts, quality assessment metrics as blur metrics are explored to classify blurred frames/images from non-blurred frames/images based on the fact that the frame loses quality due to blur artifacts. It is true that blur-affected text may not be readable. Therefore, the proposed method combines quality metrics for the input frame to estimate degrees of blur in the frame. Since the given video does not provide reference or ideal frames, the proposed method estimate the degree of blur automatically using the following quality metrics. Inspired by the metrics proposed for measuring the quality of the image without a reference image (Blanchet & Moisan, 2012; Blanchet, Moisan, & Rougé, 2008; Mittal, Moorthy, & Bovik, 2011; Mittal, Soundararajan, & Bovik, 2013), the proposed method proposes the same metrics for estimating degree of blur in the video text frame.

(i) BRISQUE (Mittal et al., 2011) (Blind/Reference less Image Spatial Quality Evaluator): BRISQUE extracts the point wise statistics of local normalized luminance

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signals and measures image naturalness based on the measured deviations from a natural image model.

(ii) NR IQA (Mittal et al., 2013) (blind/No-Reference (NR) Image Quality Assessment (IQA)): It is a model that operates in the spatial domain. BRISQUE does not compute distortion-specific features, such as ringing, blur, or blocking, but instead uses scene information of locally normalized luminance coefficients to quantify possible losses of "naturalness" in the image due to the presence of distortions. NR IQA is based on the principle that natural images possess certain regular statistical properties that are measurably modified by the presence of distortions.

(iii) GPC (Blanchet et al., 2008)(Global Phase Coherence): GPC of an image is computed by comparing the likelihood of the image to the likelihood of all possible images sharing the same Fourier power spectrum. The likelihood is measured by the total variation (Rudin-Osher-Fatemi implicit prior), and the numerical estimation is realized by a Monte-Carlo simulation.

(iv) SI (Blanchet & Moisan, 2012) (Sharpness Index): SI is closely related to the GPC difference, which uses Gaussian random fields instead of random phase images.

BRISQUE measures the naturalness of video frames; with NRIQA are able to measure the quality even though the frame is degraded by various artifacts. GPC assesses the phase shift occurrence over the frame, whereas SI uses the same methodology to measure the Gaussian random field.

The proposed method estimates the above metrics and aggregates them to obtain a single value as a quality assessment (QA) score for classifying blurred or non-blurred frames as follows. Since the scales of metrics varies from one metric to another i.e. as BRISQUE is 0-100, NRIQA is 0-100, GPC is 0-10 and SI also 0-10, values are

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normalized to the same scale to avoid loss of information. Then the proposed model aggregates the normalized values as defined in equation (1), where smaller values represent good quality images and higher values represent bad quality images. Let $\alpha, \beta, \gamma, \lambda$ be the scores received from BRISQUE, NR IQA, GPC and SI respectively. QA can be calculated as

$$QA = (\alpha + \beta + \gamma + \lambda)/n \tag{6.1}$$

where n is the number of quality measures considered, in the proposed work n is 4.

In order to automatically classify and to set a threshold value for classification, 100 frames are chosen randomly from the databases which include 50 non-blurred frames and 50 blurred-frames. Sample non-blurred and blurred frames with QA scores are shown in Figure 6.3 where it can be noticed that since the first two frames (Figure 6.3(a) and (b)) are not affected by blur, the QA score is low. It is observed from frames with QA scores in Figure 6.3(c)-(j) that as blur increases, the QA score increases. It is also observed from Figure 6.3(a)-(j) that a text detection response given by the method (Cao et al., 2015) is good for the first two frames and it becomes worse as blur increases. Based on this observation, the proposed method sets a QA score of 25.5 as a threshold to classify blurred frames from the non-blurred frames. In other words, if the QA of the input frame is more than 25.5, it is classified as a blurred frame otherwise it is classified as non-blurred frame.

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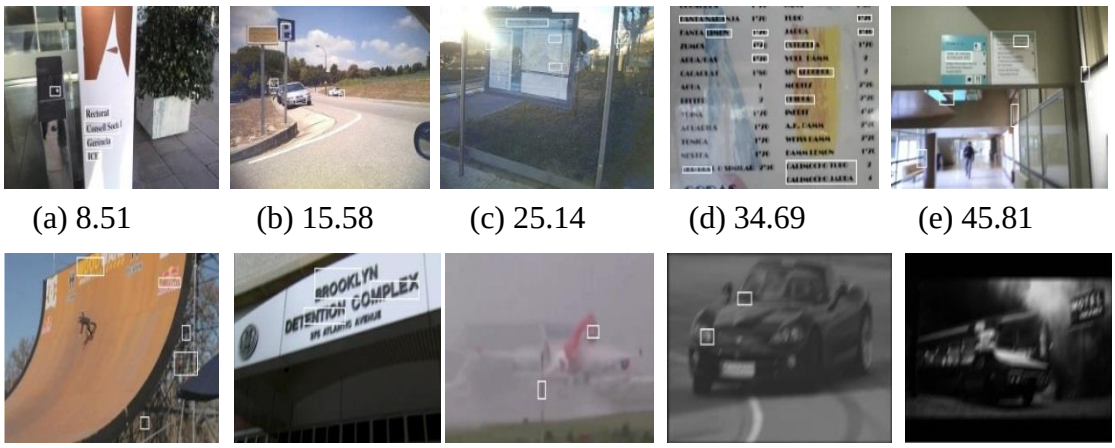

Figure 6.3: Sample images with various degree of blur with their text detection response

Overall, it is observed from the above analysis that the proposed Quality Assessment (QA) of classification of blurred and non-blurred frames is robust to different degrees of blur on a variety of images such as different types of video and natural scene images. This is because the QA is obtained by aggregating four well known metrics, which are proposed for estimating the quality of the images that are caused by different degrees of blur and distortion. For example, BRISQUE measures the naturalness of video frames, NRIQA is able to measure the quality even though the frame is degraded by various artifacts, and GPC assesses the phase shift occurrence over the frame, whereas SI uses the same methodology to measure the Gaussian random field. Since the proposed QA is an aggregation of the above-mentioned four (different) metrics, the classification of blurred and non-blurred images is robust to some extent.

6.2.2 Blind Deconvolutional Model

The method presented in the previous section classified blurred frames from the set of non-blurred frames in video or images. For this section, a blurred image is input for deriving a deblur model as follows. A classical image deblurring problem (Tang, Gong, Li, & Wang, 2014) is formulated as:

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$$g(x,y) = k(x,y) * f(x,y) \tag{6.2}$$

where, $g(x,y)$ is the blurred text image, $k(x,y)$ is the system kernel and $f(x,y)$ is the original text image. There are many popular models for restoring an image that make use of the L0 norm, L1 norm and L2 norm in the literature. For example, (J. Pan et al., 2014) proposed a model for deblurring text images by exploring the L0 norm with the gradient, where the regularizer parameter for L0 norm is $\|f(x,y)\|_0^0$, which generates the kernel for deblurring. (Y. Wang et al., 2008) proposed an L1 norm-based model for deblurring where the regularized parameter for the L1 norm is $\|f(x,y)\|_1^1$ for deriving the kernel. (Cao et al., 2015) proposed an L2 norm-based model for deblurring, where the regularizer parameter for the L2 norm is $\|f(x,y)\|_2^2$ for estimating the blurring kernel. The above state-of-the-art methods are not effective for the images which have low contrast and low illumination scenes. Therefore, in this work, the proposed method estimate the kernel by exploring an alternative minimization (AM) approach (Yun & Woo, 2011) to overcome the above problems. Here, the algorithm minimizes the energy function by alternating between the image and the kernel, till the final estimates $\hat{f}(x,y)$ and $\hat{k}(x,y)$ are obtained. This algorithm considers blurred frames as input and a delta function which is the initial point of the kernel i.e. 1 at the centre and 0 elsewhere are used as initial inputs for the optimization process through an alternating minimization approach. This section formulates the use of the proposed Gaussian weighted L1 norm in the AM algorithm. Here, first the modified energy function will be discussed, followed by the formulation of partial differential equations used for obtaining the estimates of the image and kernel.

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6.2.2.1 Kernel estimation

Inspired by the work presented in (J. Pan et al., 2014; Y. Wang et al., 2008) for deblurring text images where it proposed an automatic way to estimate the size of the kernel using an efficient minimization method, the proposed method explores the same approach to estimate the size of the kernel for blur present in video frames with a modified L1 regularizer that uses the Gaussian function as weights. The kernel, which is to be a smaller size of the image, is estimated using an energy minimization function as follows.

$$E(\hat{k}(x,y)) = \underbrace{\int_{\Omega} (\hat{k}(x,y) * f(x,y) - g(x,y))^2 dxdy}_{\text{Data}} + \underbrace{\lambda \int_{\Omega} wR(\hat{k}(x,y))dxdy}_{\text{Regular}} \quad (6.3)$$

where Ω is the image domain. The main task of restoration is to minimize this energy by obtaining an estimate of the kernel $\hat{k}(x,y)$ such that $\hat{k}(x,y) * f(x,y)$ approximates $g(x,y)$ in a least square sense. Here, λ is the regularization parameter with operator R chosen as the Gaussian weighted (*w*) L1 norm. These two parameters help us to preserve the edges by removing blur in the images. The λ is required to control the trade-off between data fidelity and the regularizer as defined in equation (6.3). Motivated by the work proposed in (Hansen, 1992) for ill-posed problems by means of the L-Curve method, the proposed method follows the same strategy for deriving values for λ in this work. The value of λ is 0.27, which is determined based on an experimental analysis in this work. *w* is the weight and is considered as the Gaussian kernel with a variance of 0.4, which is applied over the L1 norm in gradient space to increase the sharpness of the edges. It works based on the fact that pixels around the edges behave like a Gaussian due to the transition from background to foreground and vice versa (Yun & Woo, 2011).

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In summary, both λ and *w* together help to brighten images where there are edges with the R operator. This results in the removal of blur from the image. The whole process is called Gaussian-weighted L1 norm for deblurring in this work, in which λ is the regularization parameter and *w* is the weight. The selection of λ and *w* is crucial for deblurring. The different value of λ and *w* create an impact over an image, this impact can be analyze by the quality of images. For illustration quality of an image with different range of λ and *w* is shown in Figure 6.4. It can also be observed from the Figure 6.4 that for λ=0.27 and *w*=0.4, the quality score is coming least that shows the highest quality of image.

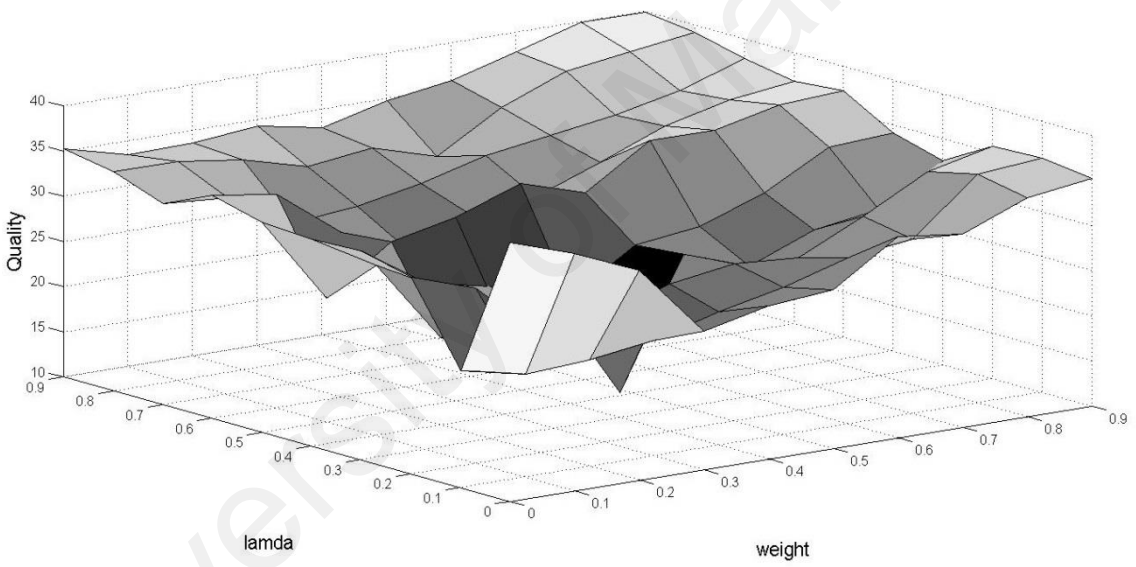

Figure 6.4: lambda (λ) and weight (*w)* impact over an image in terms of quality

This kernel estimation results in energy minimization taking the following form,

$$E(\hat{k}(x,y)) = \int_{\Omega}(\hat{k}(x,y) * f(x,y) - g(x,y))^2 dxdy + \lambda \int_{\Omega}(\left| w\nabla \hat{k}(x,y) \right|) dxdy$$

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(6.4)

With Euler-Lagrange the solution to this energy minimization problem can be obtained as:

$$\frac{\partial \hat{k}(x,y,t)}{\partial t} = -2 f(x,y) * (\hat{k}(x,y,t) * f(x,y) - g(x,y)) + \lambda(\nabla . \left(w \frac{\nabla \hat{k}(x,y,t)}{\left| \nabla \hat{k}(x,y,t) \right|} \right))$$

(6.5)

Discretization of Eqation 6.3 leads to the formulation of a partial differential equation given as,

$$\hat{k}(x,y,n+1) = \hat{k}(x,y,n) - 2(f(x,y) * (\hat{k}(x,y,n) * f(x,y) - g(x,y)) + \lambda(\nabla . \left(w \frac{\nabla \hat{k}(x,y,n)}{\left| \nabla \hat{k}(x,y,n) \right|} \right))$$

(6.6)

where *n* is the iteration number. Hence, by iterating Equation (6.6), an estimate of the kernel $\hat{k}(x,y)$ will be obtained. Sample kernel estimation and its effect on deblurring images is illustrated in Figure 6.4 where for the blurred images in Figure 6.4(a)-Figure 6.4(b), kernels of size 15×15 are used for deblurring the images as shown in Figure 6.4(c)-Figure 6.4(d), respectively. It is noted from Figure 6.4(c) and (d) that kernel estimation using the above procedure performs well.

The above procedure estimates the kernel automatically according to the degree of blur in the frames. At the same time, the method needs to determine the size of the kernel automatically as the kernel changes. It is true that if kernel is chosen of small size, then there is a possibility of losing global information; conversely if it has large size, it can lose local information. In order to find an optimal size for the kernel, the

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proposed method proposes to check QA values by varying the kernel size for the input frame. It is expected that when the input frame has no blur, the QA must give a low value according to the quality metrics. Therefore, the proposed model considers the kernel size for which the QA gives the lowest score compared to other kernel sizes, as illustrated in Figure 6.5, for the frame in Figure 6.4(a), where one can see that the QA gives the lowest score for a kernel of size 15×15. In this way, the proposed model determines size, as well as the kernel automatically for deblurring the blurred frames.

(a) Blurred Frames with QA= 44.08

(b) Blurred frame with QA= 63.29

(c) Deblurred frame with QA= 21.83

(d) Deblurred frame with QA= 13.34

Figure 6.5: Sample blurred frame and corresponding deblurred frame with the QA score of the proposed method associated with the estimated kernel of size 15×15.

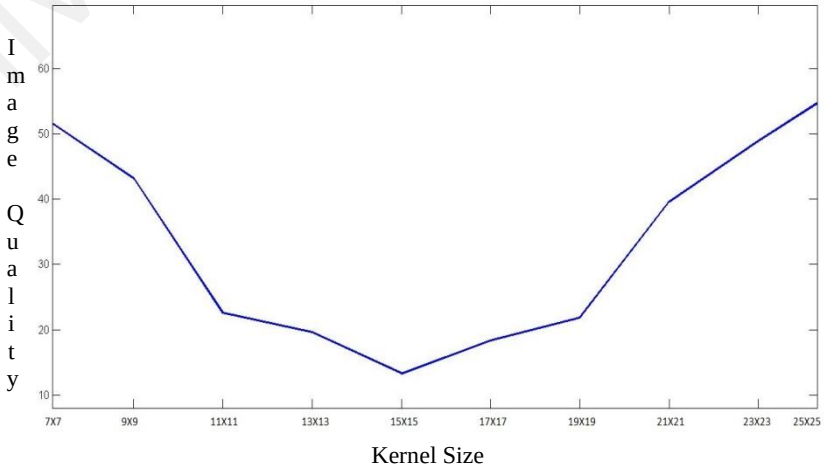

Figure 6.6: Kernel size Vs. Image quality

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6.2.2.2 Image estimation

Similarly, for image estimation the energy minimization can be written as:

$$E(\hat{f}(x,y)) = \int_{\Omega}(k(x,y) * \hat{f}(x,y) - g(x,y))^2 dxdy + \lambda \int_{\Omega}(wR(\hat{f}(x,y)))dxdy \tag{6.7}$$

where Ω is the signal domain λ is the regularization parameter and *R* is the operator chosen to be the Gaussian weighted L1 norm. This results in energy minimization of the following form,

$$E(\hat{f}(x,y)) = \int_{\Omega}(k(x,y) * \hat{f}(x,y) - g(x,y))^2 dxdy + \lambda \int_{\Omega}\left| w\nabla \hat{f}(x,y)\right| dxdy \tag{6.8}$$

The choice of selecting a Gaussian weighted L1 regularizer is its ability to effectively preserve the edges of an image.

This energy function leads to a gradient decent of the following form:

$$\frac{\partial \hat{f}(x,y,t)}{\partial t} = -2k(x,y) * (k(x,y) * \hat{f}(x,y,t) - g(x,y)) + \lambda \nabla . \left(w \frac{\nabla \hat{f}(x,y,t)}{\left|\nabla \hat{f}(x,y,t)\right|} \right) \tag{6.9}$$

On discretization of the above equation, it results in the following partial differential equation for estimating the image as,

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$$\hat{f}(x,y,n+1) = \hat{f}(x,y,n) - 2(k(x,y) * (k(x,y) * \hat{f}(x,y,n) - g(x,y)) + \lambda\nabla.\left(w\frac{\nabla \hat{f}(x,y,n)}{\left|\nabla \hat{f}(x,y,n)\right|} \right) \quad (6.10)$$

Hence, by iterating equation (10) an estimate of the image $\hat{f}(x,y)$ will be obtained.

The proposed deblurring response is shown in Figure 6.4, where it is noted that the proposed method restores fine details successfully for blurred images. It is evident from the QA score that for those blurred images shown in Figure 6.4(a) and Figure 6.4(b) it is reduced to 21.83 and 13.34 respectively, as shown in Figure 6.4(c) and Figure 6.4(d). Therefore, it can be concluded that the proposed method is sufficiently satisfactory to preserve the edge intensities which are essential for improving text detection and recognition performance.

6.3 Experimental Results and Discussion

The experiment for the proposed model is carried out on PC with the system Intel® Core™ i7-3517U CPU @1.90GHz, 2.40 GHz, 8GB RAM, 64 bit OS (Windows 7). Since there is no standard blurred data for video text detection and recognition in video, authors dataset has been created, consisting 30 videos, 15-20 seconds long results in approximately 11400 frames. In order to test effectiveness of the proposed method, standard databases are considered, namely, ICDAR 2015 (Karatzas et al., 2015) which has 24 videos, 12-15 seconds long, results in 10,800 frames, ICDAR 2013 videos (Karatzas et al., 2013) which has 15 videos, 10-15 seconds long, results in 7000 frames, YVT (Nguyen et al., 2014) videos which has 30 videos, 12-16 seconds long, results in 13,500 frames. For natural scene databases, namely, ICDAR 2013 (Karatzas et al., 2013) which has 462 images, SVT (Kai Wang & Belongie, 2010) which has 350 and

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MSRA-TD500 (Yao, Bai, Liu, Ma, & Tu, 2012) which has 500 images. In total, 42,700 video frames and 1312 scene images for evaluating the proposed method in this work.

Details of ICDAR 2015, ICDAR 2013 and YVT datasets are discussed in section 3.4.1. The ICDAR 2013 scene images include high resolution, complex backgrounds with mostly horizontal texts. The SVT dataset focuses on street view images where one can see complex backgrounds with lots of greenery and buildings. In this dataset, most of the text present in horizontal direction. The MSRA-TD 500 dataset covers a variety of scene text recorded in indoor and outdoor environments and the text is in multi-oriented directions. The main intention to choose the above diverse data is to demonstrate that the proposed method is sufficiently generic and effective in different situations.

6.3.1 Experiments on Blur Frame Classification

For this experiment, the proposed method examined each frame of the video and scene datasets considered to evaluate the proposed classification method. In total, 15805 blurred frames from video, 174 blurred images from scene data and 26895 good frames from video, 1138 images from scene data were employed. The proposed method uses the classification rate for measuring the performance of the proposed classification method. Sample qualitative results of the proposed method are shown in Figure 6.7 where it can be observe that the proposed method classifies blurred and non-blurred frames successfully.

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(a) Blur frame Our dataset (b) Blur frame YVT (c) Blur frame from ICDAR


(d) Blur from SVT (e) Non-blur from ICDAR 2013 (f) Non-blur from MSRA

Figure 6.7: Samples successful results for blur and non-blur classification by the proposed method

The quantitative results for authors video data, standard video data and scene image data in the form of a confusion matrix for the classification rates are reported in Table 6.1-Table 6.3, respectively. To determine the effect of normalization of scales of different metrics compared to the actual scale of the metrics, the proposed method calculated the classification rate through a confusion matrix using an actual scale range on three datasets as reported in Table 6.1-Table 6.3, respectively. Table 6.1-Table 6.3 show that the classification rate of actual scale range scores provide a low accuracy compared to the normalized scale range for all three datasets due to loss of information caused by different scales. This shows that normalized score is better than the actual scale range. Therefore, it can be concluded from Table 6.1-Table 6.3 that the results provided by the proposed model are encouraging as it produces a classification rate greater than 80% rate for all the datasets. Interestingly, the proposed method demonstrates consistent results despite the fact that the nature of the datasets differ in terms of resolution and backgrounds.

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Table 6.1: Confusion matrix (classification rate in %) of video frames from authors video datasets (BF: Blurred Frames; NBF: Non Blurred Frames)

Types	Normalized QA Parameters		Actual Range QA Parameters	
	CR for NBF	CR for Blurred Frame	CR for NBF	CR for BF
NBF	88.4	11.6	65.2	34.8
BF	17.4	82.6	26.3	73.7

Table 6.2: Confusion matrix (in %) of video frames from standard video datasets

	Normalized QA Parameters						Actual Range QA Parameters					
Datasets →	ICDAR2013 video		YVT		ICDAR2015 video		ICDAR2013 video		YVT		ICDAR2015 video	
	NBF	BF	NBF	BF	NBF	BF	NBF	BF	NBF	BF	NBF	BF
NBF	84.1	15.9	82.9	17.0	86.5	13.4	69.4	30.6	78.1	21.9	71.4	28.6
BF	16.5	83.5	21.8	78.2	16.3	83.6	38.7	61.3	35.3	64.7	32.9	67.1

Table 6.3: Confusion matrix (in %) of images from standard scene image datasets (BI: Blurred Image; NBI: Non-Blurred Image)

	Normalized QA Parameters						Actual Range QA Parameters					
Datasets →	ICDAR2013 scene images		SVT		MSRA-TD500		ICDAR2013 scene images		SVT		MSRA-TD500	
	NBI	BI	NBI	BI	NBI	BI	NBI	BI	NBI	BI	NBI	BI
NBI	92.49	7.51	82.29	17.71	92.8	7.2	76.5	23.5	78.4	21.6	76.1	23.9
BI	12.1	87.9	13.6	86.4	21	79	28.6	71.4	23.8	76.2	31.6	68.4

6.3.2 Experiments on Proposed Deblurring Model

For this experiment, the proposed method uses the response of proposed classification method (Section 6.3.1 and experiments discussed in section 6.4.1) for classifying blurred and non-blurred frame/images on the datasets. The classified blurred images are considered for experiments on deblurring in this section. As a result, the proposed method have got 9120, 1960, 2025, and 2700, blurred frames respectively from authors dataset, the ICDAR 2013, YVT and ICDAR 2015 video datasets.

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Similarly, 33, 22, 119 blurred scene images respectively from the ICDAR 2013, MSRA and SVT datasets were obtained. In summary, 15805 blurred frames from video and 174 blurred images from scene datasets were extracted. It is noted that blurred frames available in the video datasets are much higher than the blurred images present in the scene image datasets because generally video captured by low resolution cameras and arbitrary camera movements are more numerous as compared to still images captured with a high resolution camera.

For the purpose of measuring the quality of the deblurred images, the proposed method uses standard blind measures, namely, BRISQUE (Mittal et al., 2011), NRIQA (Mittal et al., 2013), GPC (Blanchet et al., 2008), and SI (Blanchet & Moisan, 2012) as discussed in section 6.3.1. In addition, the proposed method also uses Average Processing Time (APT) per frame for deblurring each image to evaluate the efficiency of the proposed method. To validate the usefulness of the proposed method, measures are calculated before classification, which combined both blurred and non-blurred images together, and after classification included classified blurred, deblurred by the deblurring methods and non-blurred images.

To demonstrate the effectiveness of the proposed model in terms of quality measures, the results of the proposed model is compared with the benchmark deblurring techniques, namely, the method based on L0 norm proposed by Pan et al. (J. Pan et al., 2014), which uses L0-regularized intensity and gradient blur for deblurring text images, and a method based on L2 norm proposed by Cho et al. (Cho et al., 2012) for text deblurring which takes into account the specific properties of text images. Wang et al. (Y. Wang et al., 2008) used an L1 regularizer for deblurring, Kumar et al. (Kumar et al., 2014), used moments for deblurring. The reason for selecting these methods for a comparative study is that the methods are popular and present as

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generalized methods with less constraints. Sample qualitative results of the proposed and existing methods are shown in Figure 6.7 and Figure 6.8. Figure 6.7 (a) gives QA for ground truth, (b) gives QA for blurred images and (c)-(g) are the result of the proposed and existing methods respectively. For the blurred image in Figure 6.7(b) with QA = 66.8, the proposed method gives better results with QA = 18.2 compared to other existing methods. The QA of Pan et al. is close to the QA of the proposed method, and as compared to other existing methods. However, the marginal difference in deblurring plays a vital role for improving the accuracies of the text detection and recognition methods. To show the effectiveness of the proposed deblurring model, the proposed method presents deblurring results of the proposed and existing methods for the frames having different degrees of blurred texts in Figure 6.8 where it can be seen that the results given by the proposed model appear as highly sharpened images compared to the results given by the existing methods. Therefore, the proposed model is useful for enhancing the performance of existing text detection and recognition methods for blurred frames.

The quantitative results of the proposed and existing methods on blurred images for deblurring in terms of average quality metric are reported in Table 6.4. Table 6.4 shows that the values of quality metrics for all the frames (before classification) give higher values than the deblurred frames after classification. This is valid because data before classification which involves a larger number of good images with no blur effects and a small number of blurred images, which is compared to the data after classification (blurred images). Since the contribution of good images is higher prior to classification, the metrics give low values. However, the processing time for all the frames consumes more time compared to the frames after classification because the deburring algorithm runs on all the frames prior to classification while the deblurring algorithm runs only on classified deblurred images after classification. The proposed

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method also test the deblurring model for the non-blurred frame to understand the behavior of the deblurring models on good quality images, as reported in Table 6.4. It is noted from Table 6.4 that the quality metric for non-blurred frames (after classification) scores a low value compared to the deblurred frames (after classification) and before classification. This is valid because good quality images without blur effect are the inputs for deblurring methods.

For the original blurred frames, average quality measures were: BRISQUE=63.7524, NRIQA=19.165, GPC=71.63 and SI=82.922. It can be seen from Table 6.4 that the proposed method is able to reduce the BRISQUE value lower than the existing methods, which shows the improvement in naturalness of the frame/image. The NRIQA measured the values of the proposed method and it demonstrates that blur artifacts were reduced after deblurring. Similarly GPC and SI values show that the proposed method is able to reduce the phase shift occurrence and Gaussian random field, respectively, over the frame/image.

To better visualize the local restoration effect on the edges of a deblurred frame, the 1-D profile is shown, it is a graph between the column index vs. intensity values for the row over the original image (ground truth) and deblurred images of the proposed and existing methods as shown in Figure 6.9. Figure 6.9 shows that the proposed method is closer to the ground truth when compared with other methods for all the four measures. This shows that the proposed method is better than the existing methods.

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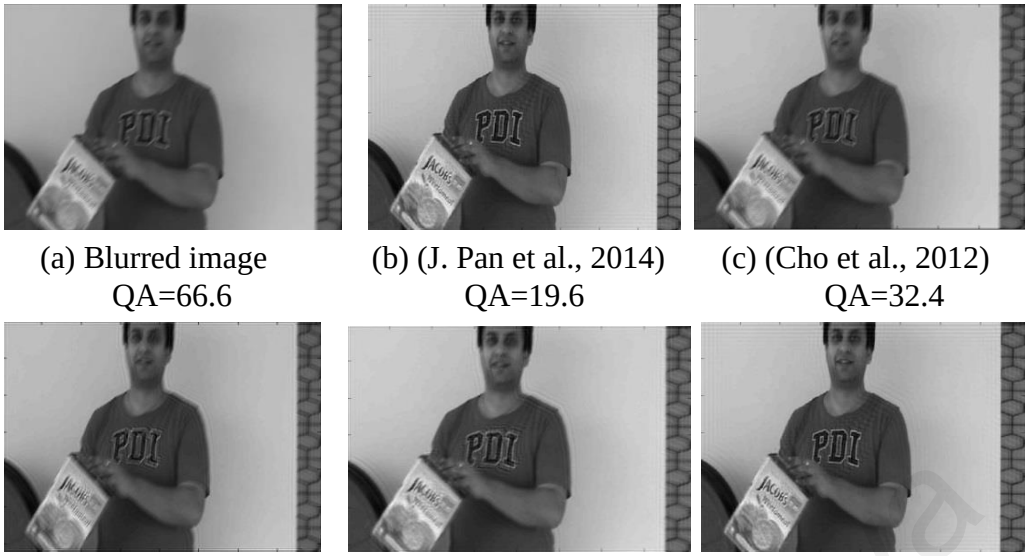

(a) Blurred image QA=66.6 (b) (J. Pan et al., 2014) QA=19.6 (c) (Cho et al., 2012) QA=32.4

(d)(Y. Wang et al., 2008) QA=26.1 (e)(Kumar et al., 2014) QA=21.7 (f) proposed QA=18.2

Figure 6.8: Deblurring performance of the proposed and existing methods

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(a) Input blur image

(b) Deblurred by (Cho, Wang, & Lee, 2012)

(c) Deblurred by (J. Pan, Hu, Su, & Yang, 2014)

(d) Deblurred by (Y. Wang, Yang, Yin, & Zhang, 2008)

(e) Deblurred by (Kumar, Paramesran, & Shakibaei, 2014)

(f) Deblurred by the proposed method

Figure 6.9: Performance of the proposed and existing methods for deblurring in comparison with the ground truth

Table 6.4: Average quality measures of the proposed and existing methods for deblurring before and after classification

Methods	Techniques	Before Classification (blurred + non-blurred frames)		After Classification (only blurred frames)		After Classification (only Non-blurred frames)	
		Average QA	APT (mins)	Average QA	APT (mins)	Average QA	APT (mins)
(J. Pan et al., 2014)	L0-norm	15.35	89.4	19.5	63.2	13.4	72.6
(Cho et al., 2012)	L2-norm	31.8	52	37.8	29.3	27.6	39.2
(Y. Wang et al., 2008)	L1-norm	24.75	58.6	37.14	26.2	22.5	43.1
(Kumar et al., 2014)	moments	21.7	73.3	24.9	52.7	19.6	55.7
Proposed Method	GW-L1-norm	15.01	55.3	19.15	24.9	13.1	35.7

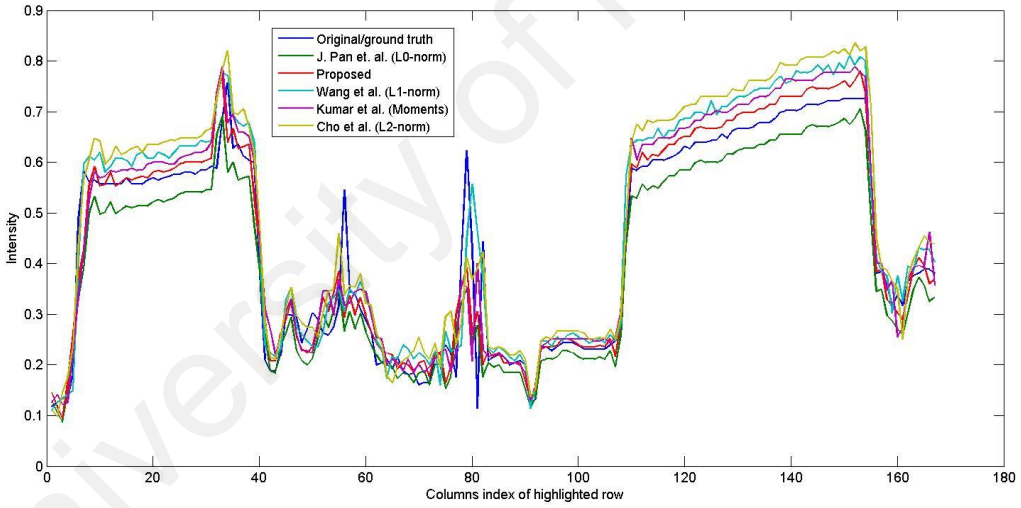

Figure 6.10: 1-D profile of existing methods with proposed

6.3.3 Text Detection Experiments for Validating the Proposed Model

Experiments in previous sections evaluated the proposed deblurring model in terms of quality metrics and classification rate. In order to illustrate the usefulness and effectiveness of the proposed model, experiments for text detection and recognition in video and natural scene images is conducted. In addition, experiments prior to classification (blurred + non-blurred) and after classification (classified blurred frames,

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deblurred frames using deblurring methods and non-blurred frames) are also conducted. Furthermore, after classification, the proposed method considers blurred images classified by the proposed classification method and their corresponding deblurred images. 9120, 1960, 2700 frames were used from authors video dataset, the ICDAR 2013 video dataset, YVT video dataset and the ICDAR 2015 video dataset, respectively. In the same way, 33, 22 and 119 were used from the ICDAR 2013 scene dataset, MSRA-TD500 and SVT datasets, respectively. In total, 15805 deblurred frames and 174 deblurred scene images were employed for conducting the experiments. The proposed method uses the same measures described in earlier chapter 3.4.2, namely, recall (R), precision (P) and f-measure (F) for evaluating the proposed method. The proposed method also implemented existing text detection methods which use different features to show that the performance of the text detection methods improves significantly after deblurring compared to before deblurring. Therefore, the proposed method computes recall, precision and f-measures before-deblurring (text detection from blurred images) and after-deblurring (text detection from deblurred images). The existing methods are Epshtein et al (Epshtein et al., 2010), which is the state-of-the-art method for text detection-based edge and gradient features in natural scene images, Liu et al. (C. Liu et al., 2005) which uses texture features for text detection in both video and natural scene images, Shivakumara et al. (P. Shivakumara et al., 2010) which uses the combination of Fourier and color for detecting text in both video as well as natural scene images, Shivakumara et al. (Palaiahnakote Shivakumara et al., 2012) which explores a Bayesian classifier for text detection in video, Zhao et al. (Z. Xu et al., 2011) which use corners and connected component analysis for caption text detection in video, Huang (X. Huang, 2011) and Mi et al. (Congjie et al., 2005) which use temporal frames for text detection in video but not in natural scene images. The main reason to choose these existing methods for experimentation is to show that the methods which

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use edge, gradient, texture, color and the combinations are sensitive to blur artifacts and the same methods give good results for deblurring. In addition methods proposed in Chapter 3, 4 & 5 are also used for evaluating the methods performance before and after classification over blur frames. Chapter 4 & 5 considers temporal information so they will be tested on video datasets only, whereas Chapter 3 response will be shown for all datasets.

Sample qualitative results of the text detection methods are shown in Figure 6.10-Figure 6.16 for the respective video data of ICDAR 2013, YVT, ICDAR 2015 and natural scene image data of ICDAR 2013, MSRA-TD500, SVT. It can be observed from Figure 6.10-Figure 6.16 that for blurred frames, text detection methods perform very poorly (before deblurring) and the same methods give good results for the deblurred images (after deblurring). This shows that the existing text detection methods are not capable of handling blurred artifacts. Since the proposed deblur model is able to preserve the edge intensities during restoration, the existing methods give better results after deblurring compared to before deblurring.

The quantitative results of the text detection methods reported in Table 6.5-Table 6.18 for authors video data, ICDAR 213 video, YVT video, ICDAR 2015 video, ICDAR 2013 scene data, MSRA data and SVT data, respectively. It is observed from Table 6.5-Table 6.18 that the conlusions are drawn from Figure 6.10-Figure 6.16 are true as recall, prcision and f-measure of the text detection methods are lower before deblurring and higher after deblurring.

Furthermore, Table 6.5-Table 6.18 show that the results prior to classification are lower than after classification (deblurred images) and higher than for blurred images. This is true because text detection methods do not perform well on blurred images due to the blurring effect. Since a higher number of good images are included prior to

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classification, and a smaller number of blurred images are used, overall the results of the text detection methods are higher than the results of those only containing blurred images. On the other hand, text detection methods give the best results for deblurred images compared to the blurred ones and all other images due to the deblurring effect. The proposed method has undertaken new experiments on non-blurred frames after classification to deblurring, text detection and recognition, respectively in Table 6.4-Table 6.23. It is observed from the experimental results on the non-blurred frames reported in Table 6.4-Table 6.23 that for the deblurring results in Table 6.4, the QA of the proposed deblurring method scores low compared to blurred frames. This results in a better quality frame that enhances the text detection rate. At the same time, one can observe that text detection rate is high for classified non-blur frames which were expected as they were not affected by blur artifacts. The experiment validates that the proposed blur frame classification and deblurring model performs well for improving text detection results.

It is noted from the results of the methods proposed in Chapter 3, Chapter 4 and Chapter 5 reported in Table 6.5-Table 6.12 for the Author's, ICDAR 2013, YVT and ICDAR 2015 video data, respectively that the method proposed in Chapter 3 scores better results in terms of recall for almost all the video datasets compared to the methods proposed in Chapter 4, Chapter 5 and other existing methods. The main reason is that it defines a new descriptor based on moments for detecting text that can work well for the images containaing blur to some extent. However, experimentation reports low results for precision compared to the methods presented in Chapter 5. This is due to the use of fixed window size. The method proposed in Chapter 4 does not report good results compared to Chapter 3 and Chapter 5 because the method is sensitive to blur and window size. On the other hand, the method proposed in Chapter 5 gives good results for almost all the video datasets in terms of F-measure compared to the methods

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in Chapter 3, Chapter 4 and other existing methods. This is because the method is insensitive to window size, the number of temporal frames unlike other methods that uses fixed number of temporal frames.

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Blurred images Deblurred images

Text Detection by (P. Shivakumara, Trung Quy, & Tan, 2010) of blurred frame and deblurred frame

Text Detection by (Palaiahnakote Shivakumara et al., 2012)

Text Detection by (Z. Xu et al., 2011) of blurred frame and deblurred frame

Text Detection by (Congjie et al., 2005) of blurred frame and deblurred frame

Text Detection by (X. Huang, 2011) of blurred frame and deblurred frame

Text Detection by (Epshtein et al., 2010) of blurred frame and deblurred frame

Text Detection by (C. Liu et al., 2005)of blurred frame and deblurred frame

Figure 6.11: Text detection Response of existing method over blurred and deblured frame on Author's dataset

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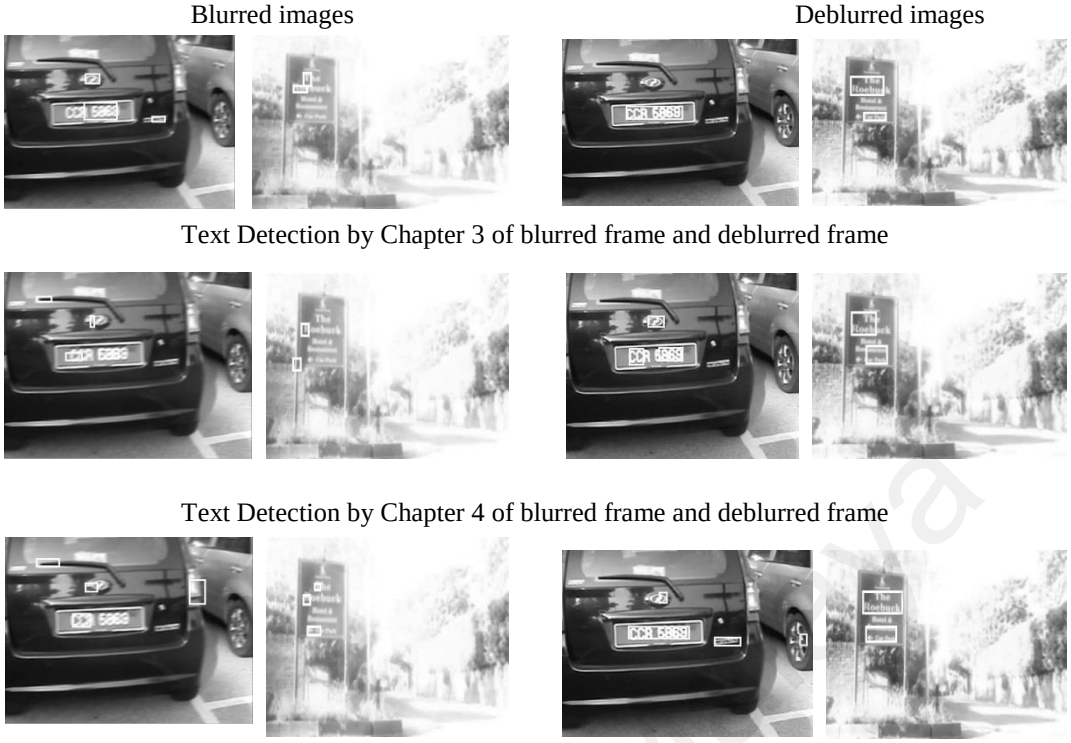

Figure 6.12: Text detection Response of proposed methods over blurred and deblured frame on Author's dataset

Table 6.5: Text detection response before classification across all frames for Author's video dataset

S. No.	Methods	Before Classification (blurred + non-blurred frames)		
		R	P	F
1	(Epshtein et al., 2010)	38.9	32.7	35.5
2	(C. Liu et al., 2005)	32.6	30.5	31.5
3	(P. Shivakumara et al., 2010)	55.7	48.9	52.0
4	(Palaiahnakote Shivakumara et al., 2012)	53.8	48.6	51.0
5	(Z. Xu et al., 2011)	49.8	50.6	50.2
6	(X. Huang, 2011)	43.1	41.7	42.3
7	(Congjie et al., 2005)	47.3	26.4	33.8
8	Chapter 3	56.2	47.2	51.7
9	Chapter 4	49.7	51.1	50.4
10	Chapter 5	54.2	50.4	52.3

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Table 6.6: Text detection response after classification across blurred and deblurred frames for Author's video dataset

S. No.	Methods	After Classification (only blurred frames)						After Classification		
		Blurred Frame			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	6.8	8.9	7.7	60.9	62.2	61.5	72.9	69.4	71.1
2	(C. Liu et al., 2005)	9.2	6.2	7.4	58.3	54.7	56.4	66.5	59.3	62.9
3	(P. Shivakumara et al., 2010)	22.6	26.7	24.4	83.4	82.1	82.7	81.9	85.3	83.6
4	(Palaiahnakote Shivakumara et al., 2012)	18.6	18.7	18.6	89.7	83.4	86.4	88.4	86.1	87.2
5	(Z. Xu et al., 2011)	19.3	17.3	18.2	80.4	79.3	79.8	80.4	81.4	80.9
6	(X. Huang, 2011)	15.5	13.6	14.4	68.3	62.9	65.4	73.2	77.4	75.3
7	(Congjie et al., 2005)	16.6	12.4	14.2	76.4	42.9	54.9	65.6	62.1	63.8
8	Chapter 3	22.1	24.4	23.2	84.9	86.3	85.6	86.7	87.3	87
9	Chapter 4	19.3	18.4	13.8	72.3	71.3	71.8	78.2	77.2	77.7
10	Chapter 5	20.3	17.6	18.9	76.9	81.3	79.1	82.4	80.6	81.5

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Blurred images Deblurred images

Text Detection by (P. Shivakumara et al., 2010) of blurred frame and deblurred frame

Text Detection by (Palaiahnakote Shivakumara, Sreedhar, Phan, Lu, & Tan, 2012) of blurred frame

Text Detection by (Z. Xu et al., 2011) of blurred frame and deblurred frame

Text Detection by (Congjie et al., 2005) of blurred frame and deblurred frame

Text Detection by (X. Huang, 2011) of blurred frame and deblurred frame

Text Detection by (Epshtein et al., 2010)of blurred frame and deblurred frame

Text Detection by (C. Liu et al., 2005) of blurred frame and deblurred frame

Figure 6. 13: Text detection Response of existing method over standard video dataset (ICDAR 2013, YVT, ICDAR2015)

Blurred images Deblurred images

Text Detection by Chapter 3 of blurred frame and deblurred frame

Text Detection by Chapter 4 of blurred frame and deblurred frame

Text Detection by Chapter 5 of blurred frame and deblurred frame

Figure 6.14: Text detection Response of proposed methods over standard video dataset (ICDAR 2013, YVT, ICDAR2015)

Table 6.7: Text detection response before classification across all frames for ICDAR2013 videos

S. No.	Methods	Before Classification (blurred + non-blurred frames)		
		R	P	F
1	(Epshtein et al., 2010)	37.0	32.7	32.8
2	(C. Liu et al., 2005)	33.1	28.6	30.6
3	(P. Shivakumara et al., 2010)	47.3	44.9	46.0
4	(Palaiahnakote Shivakumara et al., 2012)	48.6	47.1	47.8
5	(Z. Xu et al., 2011)	50.7	48.9	49.8
6	(X. Huang, 2011)	41.5	40.6	41.0
7	(Congjie et al., 2005)	42.7	36.4	39.2
8	Chapter 3	49.4	50.3	49.8
9	Chapter 4	46.7	44.9	45.8
10	Chapter 5	51.2	50.6	50.9

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Table 6.8: Text detection response after classification across blurred and deblurred frames for ICDAR2013 videos

S. No.	Methods	After Classification (only blurred frames)						After Classification		
		Blurred Frame			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	5.7	4.2	4.8	57.5	61.8	59.5	64.3	59.4	61.8
2	(C. Liu et al., 2005)	8.3	5.2	6.3	50.9	66.6	57.7	68.4	66.9	67.6
3	(P. Shivakumara et al., 2010)	28.5	37.5	32.4	82.1	83.1	82.5	84.3	81.4	82.8
4	(Palaiahnakote Shivakumara et al., 2012)	7.14	8.1	7.5	85.7	63.1	72.7	82.4	83.6	83
5	(Z. Xu et al., 2011)	17.1	21.3	19.0	78.3	79.0	78.6	79.5	72.8	76.1
6	(X. Huang, 2011)	10.5	12.7	11.4	51.3	54.5	52.8	66.5	62.5	64.5
7	(Congjie et al., 2005)	9.28	7.4	8.2	62.3	39.9	48.6	67.4	62.1	64.7
8	Chapter 3	28.3	35.9	32.1	78.3	80.4	79.3	83.1	77.3	80.2
9	Chapter 4	21.4	20.6	21.1	76.1	74.1	75.1	77.1	72.4	74.7
10	Chapter 5	25.7	24.1	24.9	77.3	75.9	76.6	81.3	75.6	78.4

Table 6.9: Text detection response before classification across all frames for the YVT dataset

S. No.	Methods	Before Classification (blurred + non-blurred frames)		
		R	P	F
1	(Epshtein et al., 2010)	41.3	36.9	38.9
2	(C. Liu et al., 2005)	38.6	34.1	36.2
3	(P. Shivakumara et al., 2010)	59.8	57.4	58.5
4	(Palaiahnakote Shivakumara et al., 2012)	58.3	54.6	56.3
5	(Z. Xu et al., 2011)	52.6	51.4	51.9
6	(X. Huang, 2011)	45.9	43.5	44.6
7	(Congjie et al., 2005)	49.6	38.3	43.2
8	Chapter 3	58.1	59.3	58.7
9	Chapter 4	55.4	50.6	53
10	Chapter 5	59.8	57.3	58.5

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Table 6.10: Text detection response after classification across blurred and deblurred frames for the YVT dataset

S. No.	Methods	After Classification (only blurred frames)						After Classification		
		Blurred Frame			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	15.2	11.6	13.1	62.5	68.2	65.2	69.4	68.3	68.8
2	(C. Liu et al., 2005)	10.3	10.3	10.3	55.7	64.3	59.7	61.1	68.2	64.6
3	(P. Shivakumara et al., 2010)	32.7	38.9	35.5	88.6	86.3	87.5	88.9	89.1	89
4	(Palaiahnakote Shivakumara et al., 2012)	27.8	22.2	24.7	86.5	72.3	69.9	82.1	79.3	80.7
5	(Z. Xu et al., 2011)	21.7	26.7	25.0	83.6	79.9	81.7	87.4	83.6	85.5
6	(X. Huang, 2011)	18.7	15.7	17.1	65.7	66.9	66.3	74.9	71.5	73.2
7	(Congjie et al., 2005)	19.4	17.7	18.1	72.8	51.1	60.0	72.3	63.5	67.9
8	Chapter 3	33.5	34.8	34.1	88.6	87.3	87.9	87.3	86.3	86.8
9	Chapter 4	28.7	25.3	27	81.3	76.4	78.5	83.1	76.1	79.6
10	Chapter 5	32.4	32.1	32.2	85.4	83.4	84.4	85.7	84.3	85

Table 6.11: Text detection response before classification across all frames for ICDAR 2015

S. No.	Methods	Before Classification (blurred + non-blurred frames)		
		R	P	F
1	(Epshtein et al., 2010)	35.7	34.5	35.1
2	(C. Liu et al., 2005)	33.1	31.8	32.4
3	(P. Shivakumara et al., 2010)	55.7	52.3	53.9
4	(Palaiahnakote Shivakumara et al., 2012)	51.4	48.6	49.9
5	(Z. Xu et al., 2011)	48.3	47.7	47.9
6	(X. Huang, 2011)	38.7	36.9	37.7
7	(Congjie et al., 2005)	37.9	35.2	36.5
8	Chapter 3	55.4	54.1	54.7
9	Chapter 4	45.6	42.1	43.8
10	Chapter 5	56.7	51.8	54.2

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Table 6.12: Text detection response before and after classification across blurred and deblurred frames for ICDAR 2015

S. No.	Methods	After Classification (only blurred frames)						After Classification		
		Blurred Frame			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	4.6	5.3	4.9	51.4	59.7	55.0	69.7	62.4	66.1
2	(C. Liu et al., 2005)	8.1	6.8	7.4	50.9	58.9	54.6	63.1	65.3	64.2
3	(P. Shivakumara et al., 2010)	26.7	35.8	30.6	81.2	81.7	81.4	84.3	82.9	83.6
4	(Palaiahnakote Shivakumara et al., 2012)	8.1	9.9	8.9	83.7	64.3	72.7	82.5	77.1	79.8
5	(Z. Xu et al., 2011)	16.9	20.8	18.6	76.6	77.9	77.2	79.1	80.5	79.8
6	(X. Huang, 2011)	8.6	11.6	9.8	52.3	54.6	53.4	62.8	61.7	62.2
7	(Congjie et al., 2005)	8.9	8.52	8.7	61.8	42.4	50.3	66.7	53.7	60.2
8	Chapter 3	25.1	28.4	26.7	84.1	81.4	82.7	85.1	81.3	83.2
9	Chapter 4	19.7	20.4	20.1	76.4	72.1	74.2	74.5	70.3	72.4
10	Chapter 5	21.3	25.6	23.4	83.1	79.4	81.2	81.9	81.4	81.6

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Blurred images Deblurred images

Text Detection by (P. Shivakumara et al., 2010) of blurred frame and deblurred frame

Text Detection by (Palaiahnakote Shivakumara et al., 2012) of blurred frame and

Text Detection by (Z. Xu et al., 2011) of blurred frame and deblurred frame

Text Detection by (Congjie et al., 2005) of blurred frame and deblurred frame

Text Detection by (X. Huang, 2011) of blurred frame and deblurred frame

Text Detection by (Epshtein et al., 2010) of blurred frame and deblurred frame

Text Detection by (C. Liu et al., 2005) of blurred frame and deblurred frame

Figure 6.15: Text detection Response of existing methods over blurred and deblured scene images from standard datasets (MSRA-TD500, SVT, ICDAR2013)

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Text Detection by Chapter 3 of blurred frame and deblurred frame

Figure 6.16: Text detection Response of proposed method of Chapter 3 over blurred and deblured scene images from standard datasets (MSRA-TD500, SVT, ICDAR2013)

Table 6.13: Text detection response before classification all frames for MSRA-TD500

S. No.	Methods	Before Classification (blurred + non-blurred images)		
		R	P	F
1	(Epshtein et al., 2010)	61.3	60.2	60.7
2	(C. Liu et al., 2005)	59.2	57.6	58.3
3	(P. Shivakumara et al., 2010)	71.3	69.2	70.2
4	(Palaiahnakote Shivakumara et al., 2012)	68.4	67.5	67.9
5	(Z. Xu et al., 2011)	70.8	66.9	68.7
6	(X. Huang, 2011)	62.6	61.5	62.0
7	(Congjie et al., 2005)	63.1	61.4	62.2
8	Chapter 3	69.3	70.4	69.8

Table 6.14: Text detection response after classification across blurred and deblurred frames for MSRA-TD500

S. No.	Methods	After Classification (only blurred images)						After Classification		
		Blurred images			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	44.3	46.1	45.2	83.2	78.4	80.7	77.1	78.9	78
2	(C. Liu et al., 2005)	38.6	40.9	39.7	81.6	76.4	78.9	72.3	76.4	74.3
3	(P. Shivakumara et al., 2010)	48.6	44.7	45.5	89.6	82.3	85.8	87.6	87.5	87.5
4	(Palaiahnakote Shivakumara et al., 2012)	46.3	44.5	45.3	86.4	78.3	82.1	84.1	81.8	82.9
5	(Z. Xu et al., 2011)	46.4	42.6	44.4	88.4	79.6	83.7	81.3	82.6	81.9
6	(X. Huang, 2011)	41.6	41.8	41.6	82.1	70.8	76.0	81.3	74.2	77.7
7	(Congjie et al., 2005)	43.2	42.1	42.6	81.4	72.9	76.9	76.3	73.1	74.7
8	Chapter 3	47.2	48.4	47.8	87.4	85.2	86.3	86.3	85.2	85.7

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Table 6.15: Text detection response before classification across all frames for SVT

S. No.	Methods	Before Classification (blurred + non-blurred images)		
		R	P	F
1	(Epshtein et al., 2010)	55.8	53.4	54.6
2	(C. Liu et al., 2005)	56.7	54.9	55.7
3	(P. Shivakumara et al., 2010)	66.8	64.9	65.8
4	(Palaiahnakote Shivakumara et al., 2012)	63.7	62.4	63.0
5	(Z. Xu et al., 2011)	58.3	57.2	57.7
6	(X. Huang, 2011)	55.4	52.5	53.9
7	(Congjie et al., 2005)	53.8	52.1	52.9
8	Chapter 3	66.3	65.2	65.7

Table 6.16: Text detection response before and after classification across blurred and deblurred frames for SVT

S. No.	Methods	After Classification (only blurred images)						After Classification		
		Blurred images			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	28.4	22.6	25.1	74.6	69.9	72.1	78.3	63.7	71
2	(C. Liu et al., 2005)	27.8	25.9	26.8	72.1	71.1	71.6	73.4	75.2	74.3
3	(P. Shivakumara et al., 2010)	35.9	38.1	38.5	86.7	84.1	85.3	86.7	87.2	86.9
4	(Palaiahnakote Shivakumara et al., 2012)	33.2	35.2	34.1	82.4	78.6	80.4	83.1	83.4	83.2
5	(Z. Xu et al., 2011)	33.8	32.7	33.2	80.4	72.3	76.1	81.7	77.3	79.5
6	(X. Huang, 2011)	34.9	25.4	29.4	74.2	72.4	73.3	73.4	78.9	76.1
7	(Congjie et al., 2005)	32.4	28.2	30.1	78.4	75.3	76.8	78.4	71.4	74.9
8	Chapter 3	34.7	35.3	35	85.6	87.3	86.4	87.1	88.2	87.6

Table 6.17: Text detection response before classification across all frames for ICDAR 2013 Scene images

S. No.	Methods	Before Classification (blurred + non-blurred images)		
		R	P	F
1	(Epshtein et al., 2010)	51.7	47.2	49.3
2	(C. Liu et al., 2005)	53.6	48.3	50.8
3	(P. Shivakumara et al., 2010)	55.9	52	53.8
4	(Palaiahnakote Shivakumara et al., 2012)	66.9	65.4	66.1
5	(Z. Xu et al., 2011)	63.7	62.1	62.8
6	(X. Huang, 2011)	55.8	53.9	54.8
7	(Congjie et al., 2005)	54.2	51.7	52.9
8	Chapter 3	67.8	65.2	66.5

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Table 6.18: Text detection response after classification across blurred and deblurred frames for ICDAR 2013 Scene images

S. No.	Methods	After Classification (only blurred images)						After Classification		
		Blurred images			Deblurred frame			Non-blurred frame		
		R	P	F	R	P	F	R	P	F
1	(Epshtein et al., 2010)	37.4	38.9	38.1	78.5	75.7	77.0	76.9	78.5	77.7
2	(C. Liu et al., 2005)	36.8	32.4	34.4	79.4	76.6	77.9	79.6	72.5	76.1
3	(P. Shivakumara et al., 2010)	42.2	48.1	44.9	89.5	88.4	88.9	89.2	88.1	88.6
4	(Palaiahnakote Shivakumara et al., 2012)	44.3	45.4	45.1	86.1	82.1	84.0	86.1	84.7	85.4
5	(Z. Xu et al., 2011)	46.3	39.3	42.5	83.6	80.9	82.2	82.1	84.9	83.5
6	(X. Huang, 2011)	18.7	15.7	17.0	65.7	66.9	66.4	75.7	71.6	73.6
7	(Congjie et al., 2005)	38.7	39.2	38.9	80.4	76.0	78.2	82.8	78.2	80.5
8	Chapter 3	45.3	42.1	43.7	88.3	87.6	87.9	87.8	88.4	88.1

Note: though Huang and Mi et al. (Congjie et al., 2005) require temporal frames for text detection, here they are used for text detection in individual frames because the main step of text candidate detection is performed for the first frame and then the same text candidates are verified with the temporal frames. Therefore, the text candidates given for the first frame are considered for text detection in this work. Since our objective is to illustrate performance before deblurring and after deblurring, the accuracy is not affected much by losing temporal frames.

It is observed from the results of the methods proposed in Chapter 3 reported in Table 6.13-Table 6.18 for the natural scene datasets of MSRA, SVT and ICDAR 3013, respectively that the method proposed in Chapter 3 scores the best results at recall, precision and F-measure for almost all the datasets compared to other existing methods. The main advantage of the method proposed in Chapter 3 is that the defined descriptor work well for both low contrast and high contrast images. Therefore, the method proposed in Chapter 3 is better than the existing methods.

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6.3.4 Text Recognition Experiments for Validating the Proposed Model

The objective of this section is the same as text detection presented in the previous section. However, for this experiment, texts lines detected by the text detection method (P. Shivakumara et al., 2010) from blurred and deblurred images are input for recognition through binarization. The method in (P. Shivakumara et al., 2010) looks good compared to other text detection methods before deblurring and after deblurring as reported in the results shown in Table 6.5-Table 6.18. Therefore, it has been chosen for text line extraction from both blurred and deblurred images. To show the usefulness of the proposed deblurring model, recognition rate is calculated at the character level using a publicly available OCR (Tesseract) for the text line images of video and natural scene datasets. The proposed method calculate the recognition rate before classification (text lines detected from both blurred + non-blurred images) and after classification (text lines detected from only deblurred images and non-blurred frames) to show the effectiveness of deblurring in improving the recognition rate for blurred images. For the after classification experiments, character recognition rate is reported before deblurring and after deblurring which also includes non-blurred frames. Several binarization methods are also implemented which are tested on text lines detected from blurred images directly (before deblurring) and text lines detected from deblurred images (after deblurring). For example, Otsu's method (Otsu, 1975), Sauvola's method (Sauvola & Pietikäinen, 2000), Wolf et al. (Wolf et al., 2002) which are baseline thresholding techniques for binarizing document images, also Bernsen (Bernsen, 1986) and Zhou et al (Y. Zhou et al., 2013) which use gray-level information for binarization. These methods are selected because most of the methods developed use these approaches as a basis for solving the problems of binarization, which includes video text line binarization and natural scene images. In addition, it is shown that the binarization methods are sensitive to blur and lead to poor results when blur is present in the images

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during binarization, and the same methods give better results for deblurred images after deblurring. When video or images contain blur, it is not easy to fix a threshold for binarization.

Sample qualitative results of binarization methods for the text lines detected from authors dataset, ICDAR 2013, YVT, ICDAR 2015, ICDAR 2013 scene images, MSRA-TD500, and SVT are shown in Figure 6.17 to Figure 6.19, respectively, where it can be seen that both binarization and recognition results are poor before deblurring compared to after deblurring. From these experiments, it can be concluded that the proposed deblurring model is essential for improving text recognition results when the image contains blur artifacts. The same conclusions can be drawn from the quantitative results of the binarization methods for the video and natural scene datasets as reported in Table 6.19-Table 6.23 where it can be seen that all binarization methods give better results after deblurring compared to before deblurring.

From the results in Table 6.5-Table 6.18 (before classification and after classification), the same conclusions are drawn for the text detection experiments as are observed for the recognition results reported in Table 6.19-Table 6.23 where one can see that the binarization methods give lower results for all the data (before classification) compared to deblurred data, and higher results compared to blurred data. It can also be observed from the results on non-blurred frames reported in Table 6.19-Table 6.23 that the recognition accuracy is higher than deblurred frames because the binarization methods work well for non-blurred frames (no blur effect). The same binarization for deblurred frames is due to the complexity of the blur. However, the difference between the recognition results on deblurred and non-blurred frames is not significant. This shows that the proposed deblurring model is effective in removing blur in frames.

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In summary, it is observed from the experiments that the performance of the text detection and binarization methods get affected when the video/image contains blur information. Therefore, in order to improve the performance of the text detection and binarization methods, deblurring is essential.

Figure 6.17: Binarization and Recognition results of the existing binarization methods for Author's dataset (Note: Recognition results are shown in box)

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Table 6.19: Recognition results before and after classification over blurring and deblurring for Author's dataset

S. No	Methods	Before Classification (blurred + non-blurred)	After Classification (only blurred frames)		After Classification
			Blurred Frame	Deblurred frame	Non-blurred frame
		Recognition Accuracy	Recognition Accuracy	Recognition Accuracy	Recognition Accuracy
1	(Otsu, 1975)	45.9	15.83	66.3	68.5
2	(Wolf et al., 2002)	42.6	15.41	62.08	65.2
3	(Sauvola & Pietikäinen, 2000)	33.5	10.6	48.5	52.7
4	(Bernsen, 1986)	35.7	12.7	50.45	56.3
5	(Y. Zhou et al., 2013)	48.7	16.2	68.91	71.4

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Blurred images Deblurred images

Text Line images of blurred and deblurred frames

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Binarization & Recognition results by (Y. Zhou et al., 2013)

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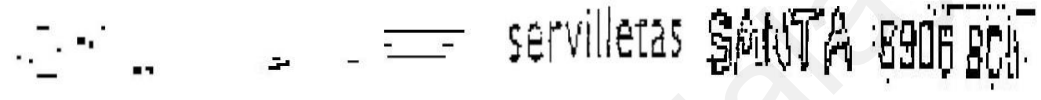
Binarization & Recognition results by Otsu's (Otsu, 1975) method



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Binarization & Recognition results by Sauvola's (Sauvola & Pietikäinen, 2000) method

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Binarization & Recognition results by Bernsen (Bernsen, 1986)

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Binarization & Recognition results by (Wolf et al., 2002)

Figure 6.18: Binarization and Recognition results of the existing binarization methods for standard video dataset (Note: Recognition results are shown in box)

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Table 6.20: Recognition accuracy before classification over all frames for standard video dataset

S.No	Methods	Before Classification (blurred + non-blurred frames))		
		Recognition Accuracy		
		ICDAR 2013	YVT	ICDAR 2015
1	(Otsu, 1975)	42.8	48.7	47.6
2	(Wolf et al., 2002)	36.8	43.6	42.3
3	(Sauvola & Pietikäinen, 2000)	34.2	35.7	34.8
4	(Bernsen, 1986)	38.9	48.3	46.1
5	(Y. Zhou et al., 2013)	51.8	52.9	52.3

Table 6.21: Recognition accuracy after classification over blurring and deblurring for a standard video dataset

S.No	Methods	After Classification (only blurred frames)						After Classification		
		Blurred Frame			Deblurred frame			Non-blurred frame		
		Recognition Accuracy			Recognition Accuracy			Recognition Accuracy		
		ICDAR 2013	YVT	ICDAR 2015	ICDAR 2013	YVT	ICDAR 2015	ICDAR 2013	YVT	ICDAR 2015
1	(Otsu, 1975)	27.4	32.6	29.5	58.1	67.3	63.7	66.9	73.4	71.5
2	(Wolf et al., 2002)	18.9	23.4	19.7	54.3	63.4	56.8	54.8	63.8	59.2
3	(Sauvola & Pietikäinen, 2000)	22.2	17.6	20.3	45.1	49.7	43.6	48.3	51.6	45.2
4	(Bernsen, 1986)	26.9	29.8	27.4	56.2	66.8	59.8	61.3	67.4	62.1
5	(Y. Zhou et al., 2013)	31.2	36.1	33.6	72.6	78.4	75.2	74.2	79.3	77.4

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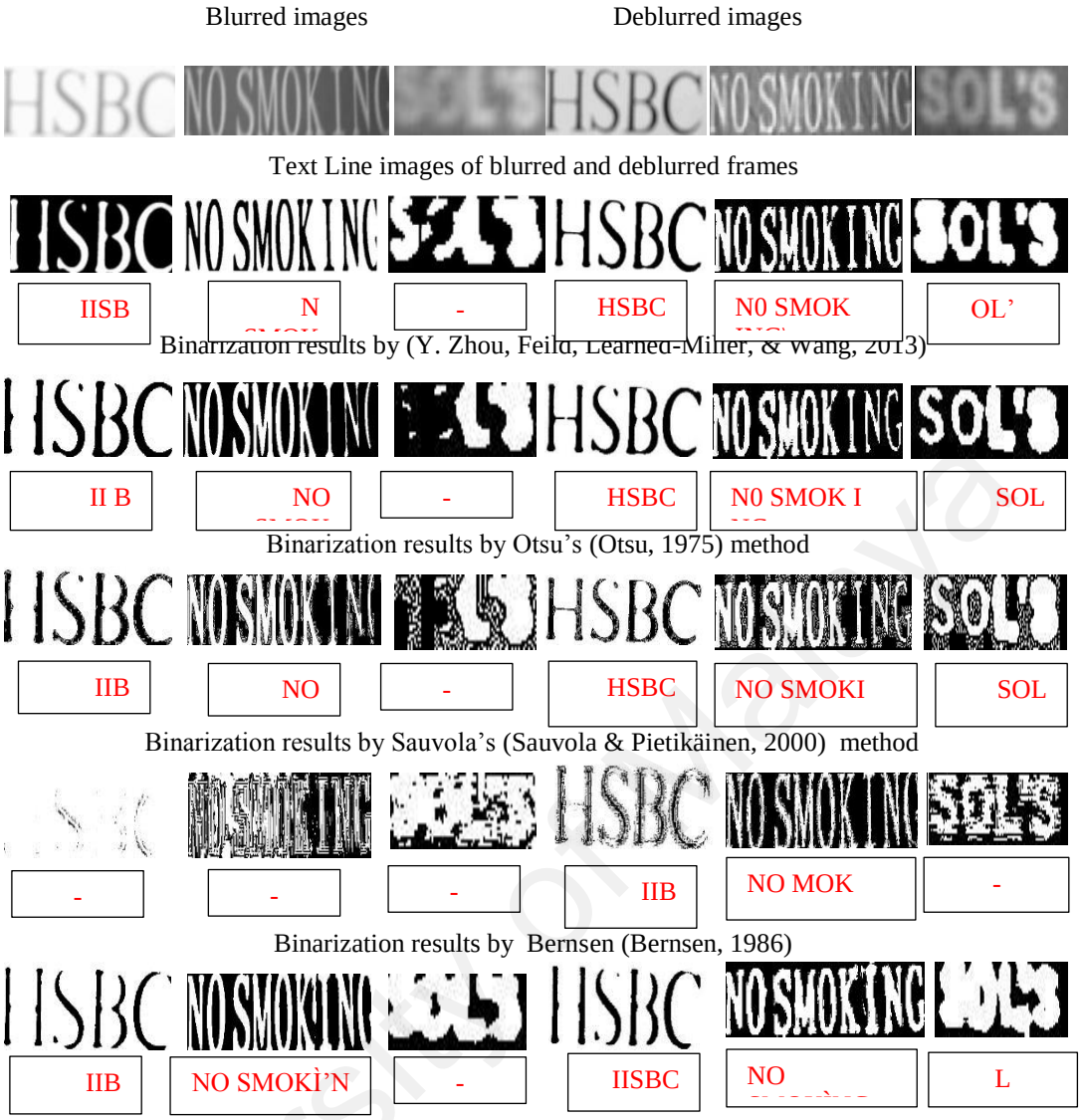

Figure 6.19: Binarization and Recognition results of the existing binarization methods for text lines from scene images

Table 6.22: Recognition accuracy before classification over all frames for standard scene dataset

S.No	Methods	Before Classification (blurred + non-blurred images))		
		Recognition Accuracy		
		MSRA-TD500	ICDAR 2013 scene	SVT
1	(Otsu, 1975)	54.7	51.6	53.7
2	(Wolf et al., 2002)	52.6	56.6	51.3
3	(Sauvola & Pietikäinen, 2000)	47.5	45.9	41.1
4	(Bernsen, 1986)	48.7	47.1	42.6
5	(Y. Zhou et al., 2013)	66.4	62.5	59.7

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Table 6.23: Recognition accuracy after classification over blurring and deblurring for a standard scene dataset

S.No	Methods	After Classification (only blurred images)						After Classification		
		Blurred images			Deblurred images			Non-blurred frame		
		Recognition Accuracy			Recognition Accuracy			Recognition Accuracy		
		MSRA - TD500	ICDAR 2013 scene	SVT	MSRA - TD500	ICDAR 2013 scene	SVT	MSRA - TD500	ICDAR 2013 scene	SVT
1	(Otsu, 1975)	31	38.1	22.4	79.4	76.2	77.3	80.8	72.5	78.3
2	(Wolf et al., 2002)	28.2	24.8	18.9	78.9	80.4	72.5	78.2	81.3	76.4
3	(Sauvola & Pietikäinen , 2000)	22.9	23.4	16.6	68.4	62.1	61.5	69.7	67.2	65.9
4	(Bernsen, 1986)	12.3	15.3	14.8	71.7	68.3	60.9	76.2	72.2	69.2
5	(Y. Zhou et al., 2013)	32.4	36.7	28.4	88.4	83.2	78.9	88.9	84.6	80.2

6.4 Summary

In this work a deblurring model which explores Gaussian weighted - L1 for restoring sharpness of the edges in blurred video/images. The proposed deblur model does not require a reference image for estimating the degree of blur in the video/images. The degree of blur estimated is used for classifying blurred and deblurred images from a pool of blurred and non-blurred frames. The experimental results of the deblurring model and classification method show that the proposed model is able to give better results than existing deblurring models. The proposed work have conducted text detection and recognition experiments using different text detection and binarization methods before deblurring and after deblurring to demostrate the usefulness and effectivenss of the proposed deblur model. The results show that the proposed deblur model helps in improving the performance of both text detection and recogntion methods.

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CHAPTER 7: CONCLUSION AND FUTURE WORK

7.1 Conclusion

In the thesis a new descriptor called Histogram of Oriented Moments (HOM) is proposed for both text detection of static and moving text detection in video in Chapter 3. The second order geometric moments are explored for deriving a new descriptor to exploits the strength of moments, such as spatial information and pixel values. However, the utilization of temporal information is limited to false positive elimination but not as main features to find text candidates.

In Chapter 4, motion vector estimation at block level is estimated for multi oriented text detection of both scene and graphics text present in video. The moments are used for finding the possible text blocks in temporal frames. Gradient direction of text pixel are explored to refine text candidates and finally region growing is proposed based on nearest neighbor criterion for restoring text line information regardless of orientation, scripts. However, the model is sensitive to window size used for moment's calculation and different scripts in videos.

Next a new method has been proposed for arbitrarily-oriented multi-lingual text detection in video based on moments and gradient directions in Chapter 5. This work proposes a new iterative procedure that utilizes the temporal information based on the fact that caption text stay at the same location for few frames while scene text has little movement from one frame to another to identify text candidates. The advantage of this iterative procedure is that it helps in identifying exact number of temporal frames to be used for text candidate detection. In addition proposed method had utilized the stroke width information for estimating window size automatically that helps in finding multi sized font text present in videos. However, the performance of the proposed method degrades in the presence of blur.

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Finally a deblur model is proposed which explores Gaussian weighted - L1 for restoring sharpness of the edges in the blur video/images in Chapter 6. The main idea is to deblur the image to improve the text detection and recognition response. The proposed deblur model does not require reference image for estimating degree of blur in the video/images. The degree of blur estimated is used for classifying blur and deblur image from the pool of blur and non-blur frames.

7.2 Future work

The work presented in this thesis is able to detect the static text and moving text present in video. However, the method assumes text appear at same location for few frames to identify the text candidates. As a result, the scope of the method is limited to the texts that have no arbitrary moments. The proposed methods do not consider text affected by occlusion because the method is not capable of restoring missing text information. The proposed method does not perform well for the video with blurred text and severe distorted texts, such as text affected by perspective distortion and camera movements.

Since a video is a collection of static images, one may think that detecting text from videos is similar as from images. Although an existing method for static images could in principle be used for detecting text from videos but videos are of different nature compared to static images. Consecutive frames present in general with small differences, while images from videos are typically worse than static images due to motion blur and out of focus issues and video compression introduces further artifacts.

The work presented in this thesis is able to find texts which are affected by motion blur but other artifacts generated by video compression and out of focus affected text are still a challenge. In the future, proposed methods can be extended for finding solution to the above mentioned limitations of the proposed method. More features can

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be proposed based on characteristics of text components which can withstand arbitrary movements of text components to track the text in video.

The future work will investigate the methods further to achieve enhanced text detection and recognition accuracies by utilizing temporal information from video. In addition, the proposed deblurring work can be extended for the images affected by non-uniform blur.

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[1] Khare, V.; Shivakumara, P.; Raveendran, P., "Multi-oriented moving text detection," Intelligent Signal Processing and Communication Systems (ISPACS), 2014 International Symposium on , vol., no., pp.347,352, 1-4 Dec. 2014.

[2] Vijeta Khare, Palaiahnakote Shivakumara, Paramesran Raveendran, "A NEW Histogram Oriented Moments descriptor for multi-oriented moving text detection in video", Expert Systems with Applications, November 2015, Pages 7627-7640.

[3] Vijeta Khare, Palaiahnakote Shivakumara, Paramesran Raveendran, Michael Blumenstein, A blind deconvolution model for scene text detection and recognition in video, Pattern Recognition, Available online 18 January 2016.

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