Dominating set based arbitrary oriented bilingual scene text localization

Roopa Mirle Jayanth[1], Mahantesh Kapanaiah[2]
[1]Department of Computer Science and Engineering, Shri Jagadguru Balagangadharanathaswamiji Institute of Technology, Bengaluru, India
[2]Department of Electronic Communication and Engineering, Shri Jagadguru Balagangadharanathaswamiji Institute of Technology, Bengaluru, India

Article Info

Article history:

Received May 27, 2021
Revised Mar 17, 2022
Accepted Mar 30, 2022

Keywords:

Arbitrary oriented text
Dominating set
Maximally stable extremal regions
Scene images

ABSTRACT

Localizing and recognizing arbitrarily oriented text in natural scene images is the biggest challenge. It is because scene texts are often erratic in shapes. This paper presents a simple and effective graph representational algorithm for detecting arbitrary-oriented text location to smoothen the text recognition process because of its high impact and simplicity of representation. An arbitrarily oriented text can be horizontal, vertical, perspective, curved (diagonal/off-diagonal), or even a combination. As a pre-processing step, image enhancement is performed in the frequency domain to improve the representation of images that are invariant to intensity. It is necessary to draw bounding boxes for each candidate character in the scene images to extract text regions. This step is carried out by utilizing the advantage of the region-based approach called maximally stable extremal regions. A typical problem with curved text localization is that non-text objects may occur within localized text regions. Our method is the first in the literature that searches for dominating sets to solve this problem. This dominating set method outperforms several traditional methods, including deep learning methods used for arbitrary text localization, on challenging datasets like 13th international conference on document analysis and recognition (ICDAR 2015), multi-script robust reading competition (MRRC), CurvedText 80 (CUTE80), and arbitrary text (ArT).

Corresponding Author:

Roopa Mirle Jayanth
Department of Computer Science and Engineering, SJB Institute of Technology
BGS Health and Education City, Kengeri, Bengaluru-560060, Karnataka, India
Email: mjroopashobith@gmail.com

1. INTRODUCTION

Text present in scene images can be in two categories into superimposed and scene text. If text is rendered artificially during the production of an image, then it is called superimposed text. If it is a part of an image, then it is scene text. Localizing and recognizing scene text is more complex compared to superimposed text as it is a part of the scene image. When scene text is in arbitrary shape, then it becomes more challenging compared to regular scene text. This grabbed the attention of researchers from the field of computer vision, pattern recognition, and artificial intelligence due to the variety of its applications like image indexing, language translators, automatic driving (navigation reading), reading assistance, and many more. Scene text reading process has two steps, the first step is extracting text which means separating text from the background, and second step is recognition of text which means making the computer recognize text. The initial step of scene text reading is to find the location of text regions. Usually, text regions are erratic. From the observations made on an arbitrary text, all text shapes are categorized mainly into perspective text and non-perspective text. The perspective text classifies as the left perspective and the right perspective. Non-perspective text is classified as vertical, horizontal, diagonal, and off-diagonal, where diagonal and off-diagonal shapes can be straight-lined or curved. Any orientation text found on any scene images should fall under any of the categories mentioned above. In Figure 1, Figure 1(a) shows the input image, while Figures 1(b) and (c) are existing system and proposed system respectively.

Figure 1. Arbitrary shaped text detection challenges (a) original image, (b) output of traditional MSER with bounding box (red box) [1], suffers from non-text object, and (c) output of DS based method (red box) includes only text objects

In literature, scene text reading manuscripts can be split into two groups. The one way is using the deep learning method detecting text blocks instead of individual characters and then grouping them into text lines [2]–[11], [12]–[15]. The other way is the traditional method localizing individual characters first and then grouped into words. These words are extracted from its background [16]–[22]. Most of the authors use deep neural network (DNN) methods for arbitrary oriented text. However, very few authors have contributed to the traditional method. Zhu and Du [15] consider the degree of blur and gradient value of points to distinguish between text and non-text regions, k-means clustering used to separate them. Then the text region is divided into four sub-regions. Finally, symmetry features are fetched by Bhattacharya distance measure to avoid misclassification. These features are input to the support vector machine (SVM) classifier for better classification. Methods [16], [17] apply Laplacian of Gaussian (LOG) to find fully connected components results in true positive text candidates by removing false positives. Basavaraju *et al.* [19] used Gaussian low pass filter and 2D discrete wavelet transform (DWT) methods for better feature extraction. Later, candidate text was extracted using k-means clustering. LOG is applied to correct disconnectivity of the text edges, and then the Euler number is computed to store true text. Finally, for segmentation Gaussian mixture model (GMM) was used. The pixel-based method [19] generates edges around the arbitrary text using standard deviation. The text line is determined using the double line structure method.

The method maximally stable extremal region (MSER) for multi-oriented text used for stable region extraction, and then it is combined with canny edge detection for enhancing text edges. Geometric properties of the text and stroke width transformation (SWT) are used to filter out non-text regions from the candidate text region [20]. However, they were not successful in case of curved text. The bounding box created around the text (red color) from existing method has a non-text object in it. To avoid this, bounding boxes for each character need to be addressed appropriately. This made to focus on this issue and successful in getting optimal box (red color) around the text (as illustrated in Figure 1) using domination graph theory. This paper brings a very simple concept of dominating set construction. This set helps in creating a precise box around any oriented text. The contributions of this paper are listed: i) proposed a simple and effective dominating set (DS) based method, ii) DS based method tested on bilingual text (English and Kannada) and iii) DS method evaluated on benchmark datasets such as 13th international conference on document analysis and recognition (ICDAR 2015), arbitrary text (ArT), CurvedText 80 (CUTE80), and multi-script robust reading competition (MRRC) datasets. The order of the paper follows research method, results, and discussion, and as the last section conclusion is summarized.

2. RESEARCH METHOD

In this section, basic terminology related to domination graph theory and then newly designed algorithms are presented. The image enhancement step reads scene image, processes it with frequency-domain filtering technique, and outputs enhanced image. The candidate text detection step uses a region-based method on enhanced image and outputs bounding boxes for each character. Bounding boxes are given for dominating set construction and selection method to extract arbitrary oriented text optimally. Then the dominating point of each bounding box is selected depending on the orientation of the text. The pendent dominating set is chosen as dominating set in case of the perspective text. If the text orientation is of non-perspective type, then isolated dominating sets are considered as dominating set. The flow diagram of the proposed method is shown in Figure 2.

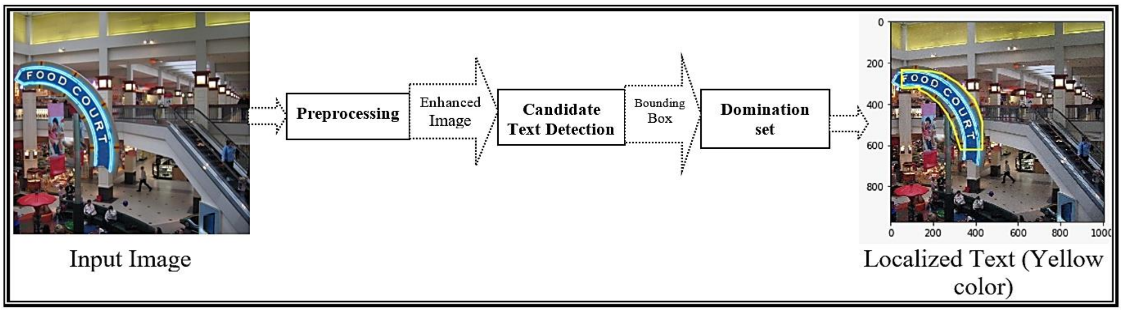


Figure 2. Flow diagram of the proposed method

2.1. Terminologies and definitions for text extraction and recognition system

Domination is a widely used concept in graph theory, with applications in psychology, computer science, nervous systems, artificial intelligence, coding theory, and decision-making theory. In a graph, the DS is a useful tool for analyzing various problems in the field, such as networking, pattern recognition, clustering, traffic planning, biological modeling, facility location problems, school bus routing, and other issues in the medical sciences. The following subsections define the terminology needed for text extraction and recognition system.

2.1.1. Definitions

Dominating set (DS): A set S is a subject of V is called as dominating set for a given graph G=(V, E), i) if it satisfies that every vertex v of V is either an element of S or ii) an adjacent to any of the element of the set S. Induced subgraph: Let us consider a graph G=(V, E), and a set $S \subset V$ be a subset of G. Then the induced subgraph G[S] is a graph with vertex set S and edge set same as E of G. Isolate dominating set (IDS): A set S is said to be an Isolate dominating set if it satisfies two condition: i) S must be dominating set and ii) There will be least one isolated vertex [23] present in induced subgraph G[S]. The example as shown in Figure 3. Pendent dominating set (PDS): A set S is said to be pendent dominating set if, i) S has to be dominating set and ii) S contains at least one pendent vertex. The example as shown in Figure 3. Maximally stable extremal region (MSER): It is one of the stable region detectors. Text present in scene image is of different sizes, different orientated, and different languages. MSER has properties such as: i) stability for a different size, ii) different language, and iii) different orientation. We were influenced by this and used MSER to detect text regions. MSER Q_i: "Let $Q_1, \dots, Q_{i-1}, Q_i \dots$ be a sequence of nested extremal regions ($Q_i \subset Q_{i-1}$). Extremal region Q_{i*} is maximally stable if $q(i)=|Q_{i+\Delta} \backslash Q_{i\Delta}|/|Q_i|$ has a local minimum at i*. Here |.| symbol represents cardinality of the set. $\Delta \in S$ is parameter of the method" [16]. Q_{i*} can be computed using (1).

$$Q_i : i* = \arg\min_i |Q_{i+\Delta} \backslash Q_{i-\Delta}|/|Q_i \quad (1)$$

All regions obtained by the MSER detector need not be text always. Some regions are text, and some are non-text due to the complexities involved in the scene images. To eliminate non-text regions two level filtering such as geometric properties of the text and stroke width variance is applied. Finally bounding box is created for potential candidate text characters. These bounding boxes of characters are combined to form text. Before constructing dominating set, following rules to be considered for finalizing bounding boxes. If a bounding box completely overlaps another, we ignore the inner bounding box and consider the outer one for future computation. If a bounding box partially overlaps with another, and their size ratio is 1:0.5 or less than said ratio's extreme, only one bounding box will replace them by taking coordinates (X_{min}, Y_{min}) and (X_{max}, Y_{max}). These finalized bounding boxes are input to the dominating set construction algorithm.

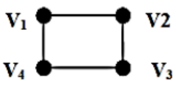
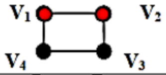
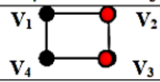
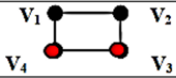
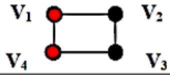
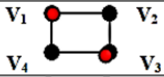
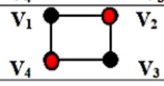
Graph : G(V, E)	All possible Dominating sets for the given graph G(V, E)	Vertices of Dominating sets are marked in red color on graph G(V, E)	Type of the dominating set
	S1={V_1,V_2}		Pendent Dominating set
	S2={V_2, V_3}		Pendent Dominating set (Used in algorithm1)
	S3={V_3,V_4}		Pendent Dominating set
	S4={V_1,V_4}		Pendent Dominating set (Used in algorithm1)
	S5={V_1,V_3}		Isolated Dominating set (Used in algorithm2)
	S6={V_2,V_4}		Isolated Dominating set (Used in algorithm2)

Figure 3. Illustrative example for dominating set construction for a given graph

2.1.2. Algorithms

This paper uses dominating set-based method to construct dominating set from each bounding box character selecting one dominating point from the upper text line and one from the bottom text line. Therefore, each character has two dominating points. For example, if a text has n number of characters, then dominating set consists of 2n+2(two corner points) points. Then all the dominating points selected need to be connected clockwise to get a polygon-shaped box around the text. Algorithms for proposed ds based arbitrary oriented bilingual text localization for both perspective and non-perspective text are given above and followed by illustrations as shown in Figures 4 and 5, respectively.

Algorithm 1. Perspective text proposed algorithm has following steps

```
Input: A set of bounding boxes of text
BB={ BB1 (V11, V12, V13, V14), BB2 (V21, V22, V23, V24), ..., BBn (Vn1, Vn2, Vn3, Vn4) }, where
Vij=(xij, yij), i=1, 2, …, n and j=1,2,4
Output: Optimal arbitrary oriented text localization.
1. For i=1 to n-1 do
2. if (x coordinate increases and yi1 and y(i+1)1 coordinates increases and yi4 and y(i+1)4
decreases)
3. dominating set=right pendent dominating set (pds) // shown in Figure 4: case 1
4. else if (x coordinate increases and yi1 and y(i+)1 coordinates decreases and yi4 and y(i+1)4
increases)
5. dominating set=left pendent dominating set (pds) // shown in Figure 4: case 2
6. else
7. apply algorithm 2
8. End For
Connect all points do start from any point move in clockwise direction and reach starting
point.
```

Algorithm 2. Non perspective text proposed algorithm has following steps

```
Input: A set of bounding boxes of text
BB={BB1 (V11, V12, V13, V14), BB2 (V21, V22, V23, V24), ..., BBn (Vn1, Vn2, Vn3, Vn4) }, where
Vij=(xij, yij), i=1, 2, …, n and j=1,2,4
Output: Optimal arbitrary oriented text localization.
1.For i=1 to n-1 do
2. If (x & y coordinates are increasing (BBi <=BB(i+1)) ) // shown in Figure 5: case 4
3. dominating set=off diagonal isolated dominating set (IDS)
4. else
5. dominating set=diagonal isolated dominating set (IDS) // shown in Figure 5: case 1, 2,
3
6. End For
7. Connect all points do start from any point move in clockwise direction and reach
starting point.
```

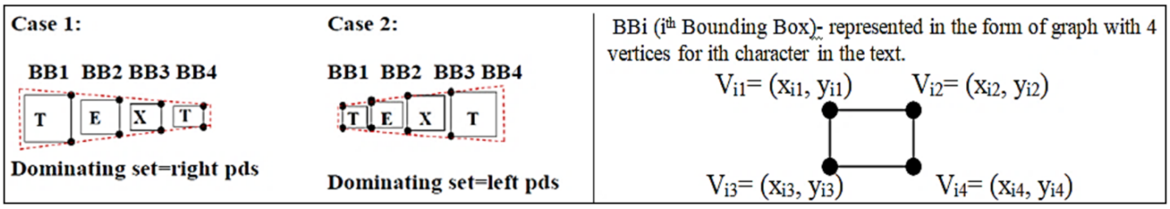


Figure 4. Illustration of perspective text

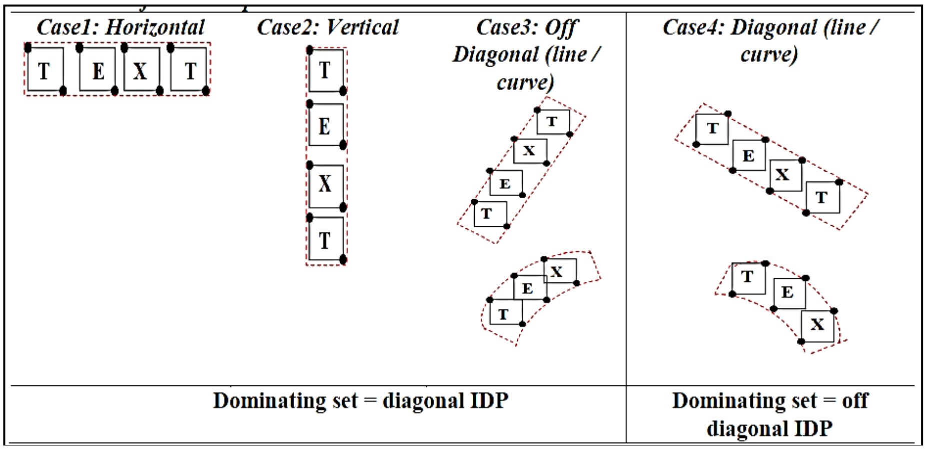


Figure 5. Illustration of non-perspective text

3. RESULTS AND DISCUSSION

In this section, the proposed DS-based method demonstrated on four benchmark datasets and their challenges. Results obtained for randomly selected images. Performance analysis with existing methods is explained in the following subsections.

3.1. Datasets

We have experimented with the proposed method on publicly available datasets such as ICDAR, Art, and CUTE-80 and regional language-MRRC dataset. The following subsections from 3.1.1 to 3.1.4 describes about datasets and their complexities. Figures 6(a) are input images randomly chosen from various datasets described in subsection 3.1.1 to 3.1.4, Figures 6(b) are the output images without DS based algorithm, and Figures 6(c) are the output images using DS based algorithm. Similarly, Figures 6(d) are input images randomly chosen, Figures 6(e) are the output images without DS based algorithm, and Figures 6(f) are the output images using DS based algorithm.

3.1.1. ICDAR2015

It includes 1,000 images for training and 500 images for testing. These are images taken by Google Glasses with improper focusing. Figure 6(c) and (f) in 3rd row shows the experimental results of the proposed method on the MRRC dataset.

3.1.2. ArT dataset

Arbitrary text (ArT) provides 10,166 images. These are taken from total-text, SCUT-CTW1500, and baidu curved scene text datasets. These images split into 5,603 images as training set and 4,563 images as testing set. Figure 6(c) and (f) in 1st row shows the experimental results of the proposed method on the MRRC dataset.

3.1.3. MRRC dataset

This dataset provides 167 images for training images and 167 images for testing. This dataset includes different language texts such as Kannada, English, Hindi, and Chinese. For the experiment, we consider bilingual (Kannada and English language) text, as it is one of the objectives of this paper. These images suffer from challenges, such as inference factors during image acquisition, environmental effects, and diversified text. Figure 6(c) and (f) in 4th row shows the experimental results of the proposed method on the Multi-script robust reading competition (MRRC) dataset.

3.1.4. CUTE80 dataset

CUTE80 is the first publicly available curved text dataset [8]. It consists of eighty curved text line images with environmental challenges that are complex background, inference factors during image acquisition such as perspective distortion and low resolution (in the circle, S, Z shaped text lines). These images are indoor or outdoor or obtained from internet sources taken from a digital camera. Results obtained from the proposed method on CUTE80 are presented in Figure 6(c) and (f) in 2nd row shows the experimental results of the proposed method.

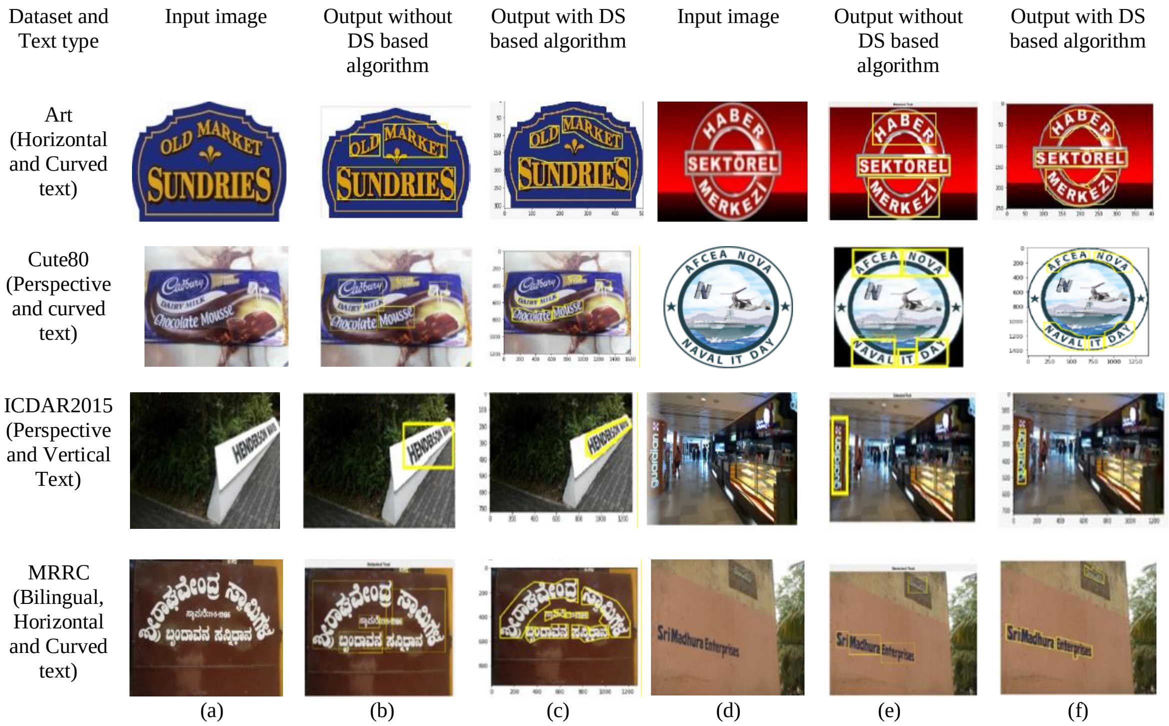


Figure 6. Localization results of the proposed method (a) input images taken from various datasets, (b) output without DS based algorithm, (c) output with DS based algorithm, (d) input image, (e) output without DS based algorithm, and (f) output with DS based algorithm

3.2. Performance analysis

Performance of the proposed algorithm is measured with precision, recall, and F-score metrics. To evaluate localization performance, precision, recall, and F-score computation are carried out using (2), (3), and (4) respectively.

$$Recall = \frac{\text{TP}}{\text{TP+ FN}} \tag{2}$$

$$P = Precision = \frac{\text{TP}}{\text{TP+ FP}} \tag{3}$$

$$F = F - measure = \frac{2*R*P}{(R+P)} \tag{4}$$

Here TP: total texts detected correctly, FN: number of texts not detected as texts, FP: number of non-texts detected as texts. The proposed dominating set-based method for text localization is experimented on the MRRC dataset to prove that it is both an orientation and language-independent method. The proposed method increases the true positive counts by reducing false-positive compare to the robust text detection technique [24] and LOG-based structural arbitrary method [16]. Precision, recall, and F-score values are given in Table 1.

Table 1. Performance comparison of DS-based method with existing methods on MRRC dataset (Kannada and English)

Methods	Precision (%)	Recall (%)	F-score (%)
Basavaraju *et al.* [16]	69.5	81.8	75.1
Yin *et al.* [24]	42.0	64.0	51.0
Proposed method	81.4	78.7	78.6

The proposed DS-based method not only improves performance by increasing recall rate and F-score rate in comparison with robust text detection technique [24], cascaded method [25], color prior guided MSER [26], and multi oriented text detection with fully convolutional network (FCN) [27]. But also shows less precision result compare to the method [27], this is due to the illumination problem in the ICDAR2015 dataset. Precision, recall, and F-score values are given in Table 2.

Table 2. Performance comparison of proposed and existing methods on ICDAR2015 dataset

Methods	Precision (%)	Recall (%)	F-score (%)
Yin *et al.* [24]	32.1	49.5	38.9
Zheng *et al.* [25]	39.5	61.6	48.1
Zhang *et al.* [26]	55.7	42.1	48.9
Zhang *et al.* [27]	71.0	43.00	54.0
Proposed method	54.6	64.3	59.1

In Figure 7, input image (refer Figure (a) and (b)), text localization results of the proposed (refer Figure (c) and (d)) and the existing methods (refer Figure (e) and (f)) for arbitrary oriented text is presented. It is also evident that DS based method creates a better boundary around irregularly shaped text as shown in Figures 7(e) and 7(f) compared to many conventional methods shown in Figures 7(c) and 7(d) with the help of powerful graph theory representation. And it shows results are encouraging to compare with existing methods.

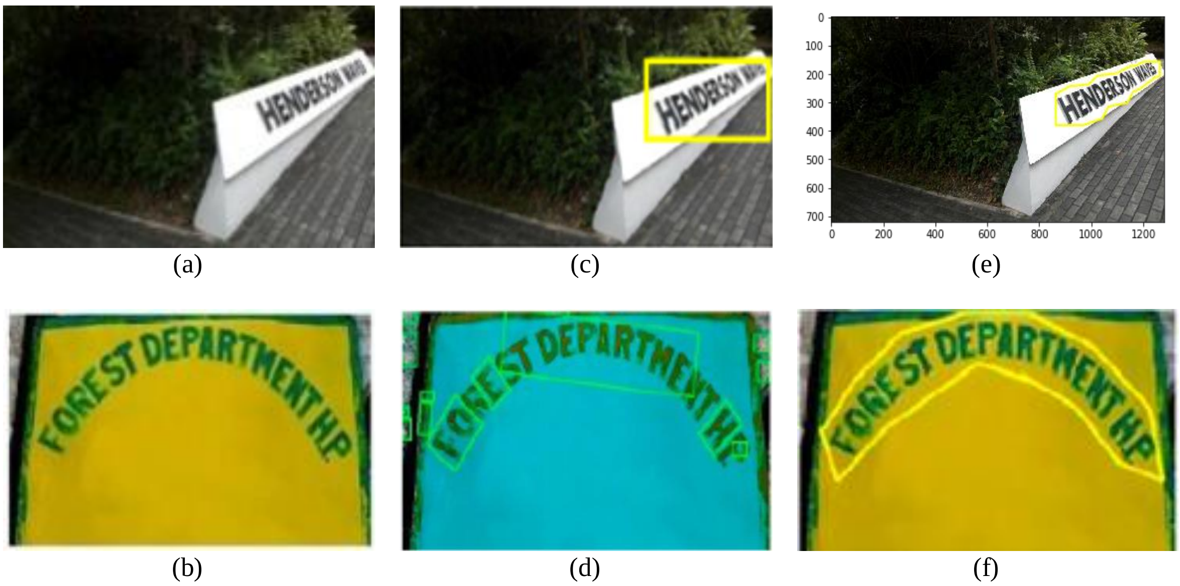


Figure 7. Text localization results of the proposed and the existing methods for arbitrary oriented text, (a) and (b) input images, (c) result of [6], (d) result of [1], (e) proposed DS based method, and (f) Proposed DS based method

4. CONCLUSION

This paper explores a novel text localization method for arbitrary oriented text in natural scene images. Dominating set construction for text localization developed in this work exploits the concept of graph theory to optimally extract text from scene images of different orientations and languages. The newly designed algorithm performed well on natural scene images that contain both English and Kannada languages. The proposed algorithm has demonstrated promising results compared to popular benchmarking techniques such as cascaded methods, MSERs with color prior guided, and multi-oriented text detection using FCNs. To increase recognition accuracy in the future, one can consider using advanced preprocessing techniques like noise removal, enhancement, and deblurring, to improve image quality. The proposed DS-based method can be applied to live video data in real-time to determine the algorithm's consistency, efficacy, and effectiveness at the development time of intelligent systems. Furthermore, domination is the one that has a practical interest and excels at analyzing various real-time problems from any of the fields if it is possible to represent the problem in terms of graphs.

REFERENCES

[1] A. Agrahari and R. Ghosh, "Multi-oriented text detection in natural scene images based on the intersection of MSER with the locally binarized image," *Procedia Computer Science*, vol. 171, pp. 322–330, 2020, doi: 10.1016/j.procs.2020.04.033.

[2] J. Chen, Z. Lian, Y. Wang, Y. Tang, and J. Xiao, "Irregular scene text detection via attention guided border labeling," *Science China Information Sciences*, vol. 62, no. 12, Dec. 2019, doi: 10.1007/s11432-019-2673-8.

[3] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 1, Dec. 2019, doi: 10.1186/s40537-019-0197-0.

[4] X. He, Y. Song, and Y. Zhang, "A coarse-to-fine scene text detection method based on skeleton-cut detector and binary-tree-search based rectification," *Pattern Recognition Letters*, vol. 112, pp. 27–33, Sep. 2018, doi: 10.1016/j.patrec.2018.05.020.

[5] Y. Liu, L. Jin, S. Zhang, C. Luo, and S. Zhang, "Curved scene text detection via transverse and longitudinal sequence connection," *Pattern Recognition*, vol. 90, pp. 337–345, Jun. 2019, doi: 10.1016/j.patcog.2019.02.002.

[6] Z. Liu, G. Lin, S. Yang, J. Feng, W. Lin, and W. L. Goh, "Learning markov clustering networks for scene text detection," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 6936–6944, doi: 10.1109/CVPR.2018.00725.

[7] Z. Liu, G. Lin, S. Yang, F. Liu, W. Lin, and W. L. Goh, "Towards robust curve text detection with conditional spatial expansion," in *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2019, vol. 2019-June, pp. 7261–7270, doi: 10.1109/CVPR.2019.00744.

[8] S. Long, J. Ruan, W. Zhang, X. He, W. Wu, and C. Yao, "TextSnake: A flexible representation for detecting text of arbitrary shapes," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 11206, 2018, pp. 19–35.

[9] P. Lyu, C. Yao, W. Wu, S. Yan, and X. Bai, "Multi-oriented scene text detection via corner localization and region segmentation," in *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, Jun. 2018, pp. 7553–7563, doi: 10.1109/CVPR.2018.00788.

[10] J. Ma *et al.*, "Arbitrary-oriented scene text detection via rotation proposals," *IEEE Transactions on Multimedia*, vol. 20, no. 11, pp. 3111–3122, Nov. 2018, doi: 10.1109/TMM.2018.2818020.

[11] X. Qin, Y. Zhou, Y. Guo, D. Wu, and W. Wang, "FC 2 RN: a fully convolutional corner refinement network for accurate multi-oriented scene text detection," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Jun. 2021, vol. 2021-June, pp. 4350–4354, doi: 10.1109/ICASSP39728.2021.9413821.

[12] J. Tang, Z. Yang, Y. Wang, Q. Zheng, Y. Xu, and X. Bai, "SegLink++: detecting dense and arbitrary-shaped scene text by instance-aware component grouping," *Pattern Recognition*, vol. 96, Dec. 2019, doi: 10.1016/j.patcog.2019.06.020.

[13] W. Wu, J. Xing, C. Yang, Y. Wang, and H. Zhou, "A scene text detector for text with arbitrary shapes," *Mathematical Problems in Engineering*, vol. 2020, pp. 1–11, Jun. 2020, doi: 10.1155/2020/8916028.

[14] D. Xing, Z. Li, X. Chen, and Y. Fang, "ArbiText: arbitrary-oriented text detection in unconstrained scene," *arXiv preprint arXiv:1711.11249*, Nov. 2017.

[15] Y. Zhu and J. Du, "TextMountain: Accurate scene text detection via instance segmentation," *Pattern Recognition*, vol. 110, Feb. 2021, doi: 10.1016/j.patcog.2020.107336.

[16] H. T. Basavaraju, D. S. Guru, and H. B. S. Harish, "LoG and structural based arbitrary oriented multilingual text detection in images/video," *International Journal of Natural Computing Research*, vol. 7, no. 3, pp. 1–16, Jul. 2018, doi: 10.4018/ijncr.2018070101.

[17] H. T. Basavaraju, V. N. Manjunath Aradhya, and D. S. Guru, "A novel arbitrary-oriented multilingual text detection in images/video," in *Advances in Intelligent Systems and Computing*, vol. 701, Springer Singapore, 2018, pp. 519–529.

[18] H. T. Basavaraju, V. N. M. Aradhya, M. S. Pavithra, D. S. Guru, and V. Bhateja, "Arbitrary oriented multilingual text detection and segmentation using level set and Gaussian mixture model," *Evolutionary Intelligence*, vol. 14, no. 2, pp. 881–894, Jun. 2021, doi: 10.1007/s12065-020-00472-y.

[19] H. T. Basavaraju, V. N. Manjunath Aradhya, and D. S. Guru, "Neighborhood pixel-based approach for arbitrary-oriented multilingual text localization," in *Advances in Intelligent Systems and Computing*, vol. 1148, Springer Singapore, 2020, pp. 1–12.

[20] M. J. Roopa and K. Mahantesh, "An impact of frequency domain filtering technique on text localization method useful for text reading from scene images," in *2019 4th International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques (ICEECCOT)*, Dec. 2019, pp. 37–43, doi: 10.1109/ICEECCOT46775.2019.9114860.

[21] A. Sain, A. K. Bhunia, P. P. Roy, and U. Pal, "Multi-oriented text detection and verification in video frames and scene images," *Neurocomputing*, vol. 275, pp. 1531–1549, Jan. 2018, doi: 10.1016/j.neucom.2017.09.089.

[22] M. Xue, P. Shivakumara, C. Zhang, T. Lu, and U. Pal, "Curved text detection in blurred/non-blurred video/scene images," *Multimedia Tools and Applications*, vol. 78, no. 18, pp. 25629–25653, Sep. 2019, doi: 10.1007/s11042-019-7721-2.

[23] M. N. Puttaswamy and S. R. Nayaka, "Isolated domination polynomial of a graph," *Inernational Journal of mathematics and Applications*, vol. 8, no. 4, pp. 69–73, 2020.

[24] X. C. Yin, X. Yin, K. Huang, and H. W. Hao, "Robust text detection in natural scene images," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 36, no. 5, pp. 970–983, May 2014, doi: 10.1109/TPAMI.2013.182.

[25] Y. Zheng, Q. Li, J. Liu, H. Liu, G. Li, and S. Zhang, "A cascaded method for text detection in natural scene images," *Neurocomputing*, vol. 238, pp. 307–315, May 2017, doi: 10.1016/j.neucom.2017.01.066.

[26] X. Zhang, X. Gao, and C. Tian, "Text detection in natural scene images based on color prior guided MSER," *Neurocomputing*, vol. 307, pp. 61–71, Sep. 2018, doi: 10.1016/j.neucom.2018.03.070.

[27] Z. Zhang, C. Zhang, W. Shen, C. Yao, W. Liu, and X. Bai, "Multi-oriented text detection with fully convolutional networks," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 4159–4167, doi: 10.1109/CVPR.2016.451.

BIOGRAPHIES OF AUTHORS

Roopa Mirle Jayanth received M.Sc. degree in Mathematics in 2001 and M.Tech. degree in Computer Science and Technology in 2003 from the University of Mysore. She is currently working as an Associate Professor, Department of Computer Science and Engineering in SJB Institute of Technology, Bangalore. She is having around 18+ years of teaching experience. She is currently a Ph.D. scholar in Computer Science and Engineering at Visvesaraya Technological University, Belagavi, Karnataka. Her research area mainly includes image processing, machine learning, computer vision, and pattern recognition. She can be contacted at email: mjroopashobith@gmail.com.

Mahantesh Kapanaiah holds a B.E. (Electrical and Electronics), M.Tech. and Ph.D. (CSE) from Visvesaraya Technological University, Karnataka, India. He is currently in the Faculty Role of the Department of E and CE at SJB Institute of Technology, Bsngalore. His research interests include Signal Processing, Digital Image Processing and Computer Vision, Machine Learning, Pattern Recognition, and Biomedical Signal Processing. He has published more than 30+ articles in peer-reviewed, international journals/conferences having high impact factors. He has served as organizing chair, symposium/session chair, and reviewer for several reputed International conferences/journals. His main goal is to take a systemic, research-based inter-disciplinary approach to innovation in engineering, recognizing the importance of various approaches to meet our society's diverse technological needs. He can be contacted at email: mahantesh.sjbit@gmail.com.