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Segmentation of Salient Flying Objects in Complex Sky Scene using Reconstruction Morphological Operations

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***Abstract*—** Salient object segmentation is useful for supervised learning process. The challenging issues of this work is small flying object Segmentation in different lighting condition in the sky images using Morphological Closing and reconstruction techniques. In the proposed method, detection of regional maximal in grey level image with specified connectivity and removing of borders, filled holes. Finally, identifies flying object and gives fast processing and effective results. Experimental results on dataset demonstrates the proposed techniques performs well against existing methods.

***Keywords*—** Birds, Grayscale reconstruction, Morphological operation.

I. Introduction

Salient object segmentation is one of the most significant and dynamic research topics in computer vision and comprehensive applications on image retrieval, object recognition, context-aware image editing, image compression [16]. Salient object segmentation is usually taken in computer vision as a process that classified into two stages First, detect of the most salient object region. Secondly, segmentation of the exact region of the object. Rarely, however, models explicitly discriminate between these two stages [1,2,18]. It is an important problem in computer vision for more than two decades. Its goal is to locate the most salient or interesting region in an image that captures the viewers' visual attention [4,13]. It is the task of focusing and segmenting the most noticeable foreground objects from a scene. The growth of salient region detection has been stimulated by the concepts of human visual perception [8]. Saliency detection has recently attracted a good quantity of analysis interest. The reason behind this increasing quality lies the effective use of those models in computer vision task like image segmentation, video summarization and compression, object detection [2]. Saliency models are broadly classified into two categories: human eye fixation prediction and salient object detection. According to the saliency model, input types are classified into two static and dynamic distinction models. whereas static models take still images as input, dynamic models work on video sequences. The good saliency detection model should have satisfied at least the following three criteria: 1) good detection: to identify the salient region and suppressed background region. 2) high resolution: saliency maps should have the high or full resolution to accurately locate salient objects and hold original image information, and 3) computational efficiency: models should detect salient regions rapidly. Salient objects segmentation semantic scene labeling, or semantic segmentation is one of the very well researched areas. In this paper, the author proposes method is experimentally demonstrates with a bird dataset which is constructed different light variation condition. It has been shown that the detector-based method using Morphological Closing and Reconstruction techniques and it gives significantly good results in the bird detection task and focus on detecting long distance flying bird object regions in the sky background.

In the rest of this paper, described introduction in section 1. Related work briefly in Section 2, proposed methodology discussed in section 3. Experimental result illustrated in section 4. Finally, concluded the paper in Section 5.

II. Related Work

In [1], proposed comparison based on qualitatively and quantitatively for 41 state-of-the-art models. Consider seven challenging datasets for benchmarking salient object detection. In [2], proposed method automatic segmentation framework for a general-purpose visual system. Segmentation techniques carried out in two stages. In the first stage all visual cues area unit combined to get the probabilistic boundary edge map of the image scene and in the second stage by using edge map, the "optimal" closed contour around a given fixation purpose is found. In [3], presented paper to tackles the problem of bird detection in large landscape images for applications in the wind energy industry. While significant progress in image recognition has been made by deep convolutional neural networks, small object detection remains a problem, so that authors follow the idea that a detector can be altered to small objects of interest and semantic segmentation methods can be used to recognize large background areas. Specifically, train a CNN detector, fully convolutional networks, and a super pixel-based semantic segmentation method. In [4], proposed estimations of 13 techniques for bottom-up salience models and a Multiscale Contrast Conspicuity (MCC) metric are compared with human visual conspicuity measurements. In [5], presented an algorithm for segmentation of the airway tree by using for morphological filtering and reconstruction. In [6], proposed algorithms to automate the segmentation Computed Tomography (CT) images. grayscale reconstruction operator to extract potential tree regions in every of the CT images. In [7], presented description of a complete automatic technique for segmenting the airway tree in three-dimensional (3-D) CT images of the thorax. Author tend to use grayscale morphological reconstruction to spot candidate airways on CT slices then reconstruct a connected 3-D airway tree. In [8], explained a novel method to automatically detect salient regions of an image via high dimensional color transform. Techniques make on salience map of an image as a linear combination of high-dimensional color space wherever salient regions and backgrounds can be distinctively separated. The author explained that linearly separation the salient regions from the background by finding an optimum linear combination of color coefficients within the high-dimensional color space and high dimensional color space integrates multiple color representations as well as RGB, CIELab, HSV and with gamma, corrections to improve its demonstrative power. Experimental results conducted on three benchmark datasets proved that technique is effective, and it is computationally efficient in comparison to previous up-to-date techniques. In [9], grayscale reconstruction is introduced two complete different proper definitions. Grayscale reconstruction in numerous image processing applications discussed to demonstrate the usefulness of this transformation for image filtering and segmentation tasks. In [10], discussed list of the summary of the existing techniques to compute it is provided, and Grayscale reconstruction is the hybrid algorithm to compare the existing algorithm. In [11], presented a method for automatically extracting salient object region from an image, which are casted in an energy minimization framework. Distinct most previous methods that only leverage appearance cues, authors employ an auto-context cue as a complementary data term. Promoting from a generic prominence saliency model for bootstrapping, the segmentation of the salient object and therefore the learning of the auto-context model area unit iteratively performed with non-user involvement. Upon conjunction, experimental results give not only a clear separation of the salient object but also an auto-context classifier which can be used to recognize the same type of object in other images. In [12], proposed recognition of salient bird objects in sky using neural network. Here flying objects segmented by otsu's method, extract texture features and recognition salient birds. In [13], author analysis from a computational perception. The basic concepts of attention implemented in these models. Presented a taxonomy of nearly 65 models, which used a critical comparison of approaches, their capabilities, and shortcomings. Thirteen principles derived from behavioral and computational studies are framed for qualitative comparison of attention models. In [14], proposed a combination of visual attention techniques and active segmentation. Active segmentation has introduced a state-of-the-art technique about inside-out segmentation, but the author had to manually specify the initial fixations to make the algorithm work. So, visual attention techniques are used to grant active segmentation automatic ability. In [15], author proposed a method for salient region detection that produced full resolution saliency maps with exact boundaries of salient objects. These boundaries are well-preserved by retaining significantly more frequency content from the original image than other existing techniques. In [16], proposed a novel graph-based ranking method to notice and segment the most salient object in an image according to its relationship to background regions. The author used regions/super-pixels as graph nodes which are fully connected to enable both long-range and short-range relations to be modeled. The relationship of every region to the image background can be caluclated in two stages. Firstly, ranking with hard background queries and secondly, ranking with soft foreground queries. In [17], proposed a deep learning model more efficiently detect salient regions in videos. It addresses two important issues, initially the deep video saliency model training with the absence of sufficiently large and pixel-wise annotated video data. Then, fast video saliency training and detection. The proposed deep video network consists of two parts, for capturing the spatial and temporal saliency information, correspondingly. In [18], proposed the Secrets of Salient Object Segmentation. Estimation of fixation prediction and salient object segmentation procedures as well as statistics of major datasets and analysis identifies serious design flaws of existing salient object benchmarks, called the dataset design bias, by overemphasizing the stereotypical concepts of saliency.

III. METHODOLOGY

To the best of the author's knowledge, previous work shows that it is very difficult for detection and segmentation of salient object images in long distance [3]. In this work, considered flying bird objects. The bird's fly's in different lighting variation condition like during sunrise, sunset and sunshine, which includes migrate birds using morphological closing and reconstruction techniques. The algorithm for the proposed methodology is shown below.

STEP.1: Birds Gray-scale image as an input.
STEP.2: False function applied for original image.
STEP.3: Calculate maximum radius and minimum radius processing using every second kernel.
STEP.4: Generating circular kernel.
STEP.5: Greyscale closing operation applied to the image for Image is reconstruction.
STEP.6: Reconstructed image using a 4-connected kernel in the dilation.
STEP.7: Calculate difference between reconstruction image and gray-scale image.
STEP.8: Find maximum value and minimum value in the difference image.
STEP.9: 20% of the difference between the minimum and maximum value.
STEP.10: Adding threshold to the false image.
STEP.11: Obtain segmentation of birds.

A. *Morphological Operation*

Morphological image process is a variety of non-linear operations associated to the shape or morphology of features in an image, such as skeletons, boundaries, etc. In any given technique, probe an image with a small shape or template called a structuring element, that defines the region of interest or neighborhood around a pixel. The basic morphological operations, convex hull, dilation, erosion, opening, closing, white tophat, skeletonize and black tophat.
Grayscale reconstruction [9,10] is an extension of binary reconstruction. Binary grayscale reconstruction is the application of successive dilations within objects of a binary image as shown in equation (1).

$$\rho_B(X) = \lim_{n \to \infty} \partial_B^n(X) \qquad (1)$$

Where $\partial_B^{(1)}(X) = (X \oplus K) \cap B$ and $\partial_B^{(n)}(X) = \partial_B \circ \partial_B \circ \partial_B(X)$ for n times, and the marker (X) is a subset of the mask (B). The marker (X) is made up of seed points – that is, where the dilation starts in the object. The mask is generally the image that is being operated. K is a Structuring Element used in the dilation and $\oplus$ is the dilation operator. Mask and marker shown in figure 1.
Above definition is expanded for greyscale reconstruction [9,10]. In this study, Grayscale image is given input for demonstration. False function applied for images after processing using every second kernel to identify maximum and minimum radius. Maximum radius considered for circle kernel and grayscale closing function of the image of interest is used as the marker image [6,7], as shown in equations (2).

$$Y = B \bullet D = (B \oplus D) \ominus D \qquad (2)$$

A marker and mask image are used where every pixel in the marker image has a pixel intensity less than or equal to the intensity of the corresponding pixel in the mask image. The marker and mask images are then threshold over a range of thresholds and binary reconstruction is performed on each threshold. The maximum intensities pixel of the binary reconstructed image forms the greyscale reconstructed image. With a good choice of a marker image, this method can be used to create a reconstructed image with the intensity peaks removed. This can then be subtracted from the original image to enhance the peaks. Fig. 1 is a diagram for greyscale reconstruction in one dimension and shows the Mask and Marker greyscale values. The reconstructed image is denoted by the shaded area.

Where X is the marker image, B is the original image (used in reconstruction as the mask image) and D is the Structuring Element. D will control the shape of the marker image and therefore objects are enhanced in the reconstruction since the difference between the original image and the reconstructed image gives segmented image [6,7].

Therefore, morphological reconstruction was applied using marker images produced using a range of Structuring Elements. The smallest Structuring Element chosen in this study is a 4-connected binary Structuring Element. Larger Structuring Elements are created by applying successive dilations to the smallest Structuring Element i.e. $D_n = D \oplus D \oplus ... \oplus D_n$ times. As described earlier, reconstruction is applied to the range of marker images for each slice. Each reconstructed image is subtracted from the original image to enhance objects in images. These subtracted images are threshold and the union of the threshold images provides segmented objects locations. The threshold value is obtained from this threshold fraction in terms of the minimum and maximum greyscale values in the reconstructed image [5].

$$\theta = \theta_0 * (MaxValue - MinValue) + MinValue, \qquad (3)$$

where θ is the threshold value

θ_0 is Threshold sensitivity, between 0 and 1, where 0 is most sensitive

IV. Experimental Results

In this paper, discussed segmentation of salient objects using morphological closing and reconstruction techniques. A large body of past research was reviewed on detection of salient objects in last few years on computer vision. Author consider only sky background images and to detect salient objects. Here demonstrated detection of small birds in different environment condition like sunrise, sunset and sunshine. Author created new bird dataset images using video converted into frames have been considered and 179 images are used to conduct an experiment. Figure 2-6 shows detect salient small birds object in natural images and experiment is performed on Intel Core i-7 6700, 3.40 GHz processor and 8 GB RAM with windows 8.1 as an operating system. The collected bird dataset images are resized to 255 X 255 size of pixel resolution to improve the algorithm accuracy. Figure 2 shows Sample experimental results for detection of flying birds in long distance. Figure 3 shows Sample experimental results for detection of flying birds in Sunrise time. Figure. 4 shows Sample experimental results for detection of flying birds sitting on electrical wire. Figure 5 shows Sample experimental results for detection of flying enormous birds. Figure 6 shows Sample experimental results for detection of flying birds in sunset time.

A. Ground truth

It is important to provide a single user interface with consistent capabilities for the experiment allowing participants to segment ground truth objects in a uniform way using different algorithms. To this end, developed a stand-alone scribble-based interactive segmentation application. The tool supports any segmentation technique that can be adapted to use a scribble driven interaction paradigm for providing iterative updates.

To extract and object from an image, users mark foreground pixels using the left mouse button, and background pixels using the right mouse button, or by using the left button while depressing the Ctrl key. As each interaction is provided the corresponding segmentation mask is updated. The segmentation can be visualized within the tool in various ways, including a hybrid-view showing the segmentation mask transparently overlaid on the image, a view showing the object borders, and a view of the object with background elements removed

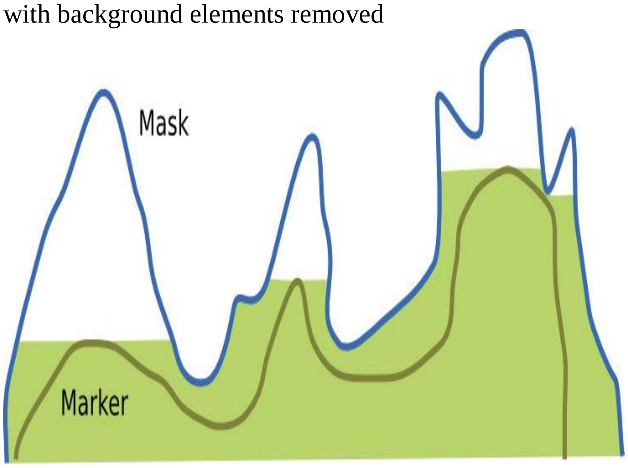

Figure. 1: Grayscale reconstruction.

B Results and Evaluation:

The dataset that includes video sequences (sunset image, sunrise image, sunshine image) [19] and ground truth collected in interactive segmentation application was used to evaluate the performance of salient object detection. In the proposed work, considered a new performance evaluation are created. Segmented Object (SO), Non- Segmented object (NSO), number of noise background images.

Table 1 shows the results of the performance evaluation of proposed technique for the collected video dataset. Experimental results show that the proposed method has the average Segmented object rate and Non- Segmented rate are 98.41 % and 1.59 %, respectively and background noise rate less. The proposed method has good performance in terms of detected rate and non-detected rate compared to other techniques. Table 2 describes Global thresholding techniques evaluation of collected video dataset images. Table 3 shows Frequency-tuned techniques evaluation of collected video datasets.

To illustrate the performance of salient object detection, the Segmented Object rate SO and the false Segmented rate NSO is adopt as defined below:

$$SO\% = \left[\frac{SO}{N}\right] X100 \tag{4}$$

$$NSO\% = \left[\frac{NSO}{N}\right] X100 \tag{5}$$

where N is the total number of salient flying objects, Segmented Object (SO) is the total number of correctly segmented salient flying objects, and Non-Segmented Object (NSO) is the total number of non-segmented salient flying objects, I is number of images.

To calculate Background Noise Image Shown in Equation (6):

$$\sum f(x) = \sum O(x) - \sum S(x) \tag{6}$$

Where $\sum f(x)$ = Background noise image.
Where $\sum O(x)$ = Original image.
Where $\sum S(x)$ = segmented image.

Figure 7 shows the qualitative results for flying birds image taken at sunset time with background noise, showing that Global thresholding techniques segmented some flying salient birds with background noise, but proposed work detects all flying salient birds without background noises like buildings [12].

Figure 8 shows the qualitative results for flying birds image taken at sunset time with background noise, showing that Frequency-tuned method segmented all flying salient birds with background noise, but proposed work detects all flying salient birds without background noises like buildings [15].

Table 1: Proposed method performance evaluation of the collected video dataset.

Complex Scene	*NI*	N	*SO*	*NSO*	*SO (%)*	*NSO (%)*	*NUMBER OF NOISE BACKGRO-UND IMAGE*
Sunset Images	**41**	**72**	**69**	**3**	**95.83**	**4.17**	**3**

Sunrise Images	**39**	**167**	**166**	**1**	**99.40**	**0.60**	**4**
Sunshine images	**99**	**151**	**151**	**0**	**100**	**0**	**0**
				Average	**98.41**	**1.59**	**7**

Table 2: Global thresholding techniques performance evaluation of the collected video dataset.

Complex Scene	***NI***	N	***SO***	***NSO***	***SO (%)***	***NSO (%)***	***NUMBER OF NOISE BACKGRO-UND IMAGE***
Sunset Images	**41**	**72**	**39**	**33**	**54.16**	**45.84**	**41**
Sunrise Images	**39**	**167**	**131**	**36**	**78.44**	**21.56**	**39**
Sunshine images	**99**	**151**	**40**	**111**	**26.49**	**73.51**	**99**
				Average	**53.03**	**46.97**	**262**

Table 3: Frequency-tuned techniques performance evaluation of the collected video dataset.

Complex Scene	***NI***	N	***SO***	***NSO***	***SO (%)***	***NSO (%)***	***NUMBER OF NOISE BACKGRO-UND IMAGE***
Sunset Images	**41**	**72**	**60**	**12**	**83.33**	**16.67**	**41**
Sunrise Images	**39**	**167**	**163**	**4**	**97.60**	**2.40**	**39**
Sunshine images	**99**	**151**	**151**	**0**	**100**	**0**	**99**
				Average	**93.64**	**6.36**	**262**

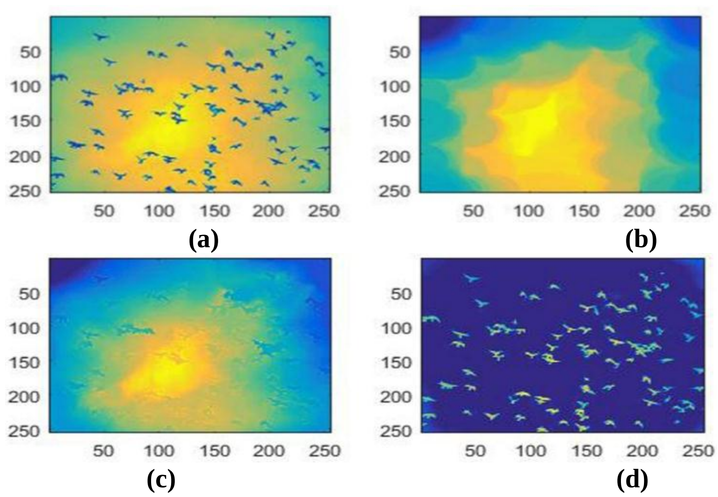

Figure.2: Detection of flying birds with long distance. (a) Original image with varying background and foreground objects. (b) Reconstructed image with circular regions removed. (c) Difference image between original and reconstructed. (d) Segmented objects.

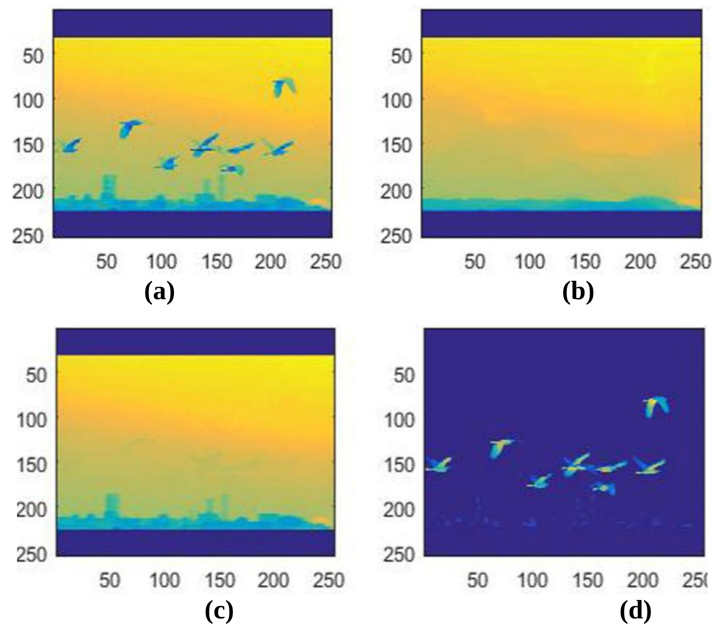

Figure.3: Detection of flying birds during Sunrise time. (a) Original image with varying background and foreground objects. (b) Reconstructed image with circular regions removed. (c) Difference image between original and reconstructed. (d) Segmented objects.

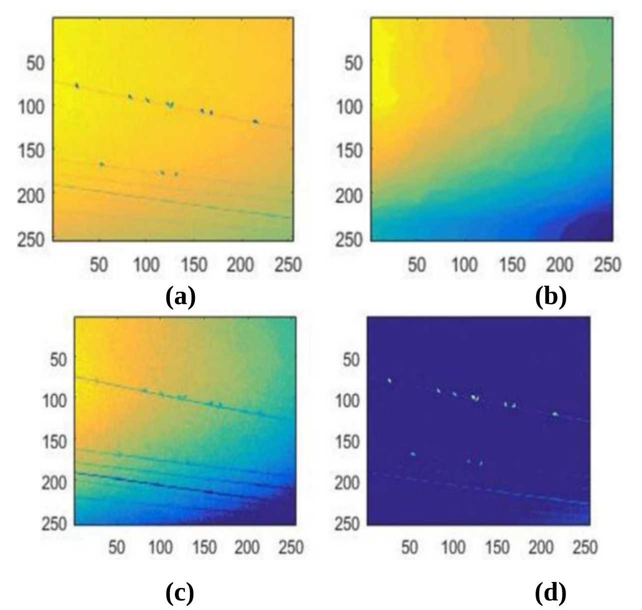

Figure. 4: Detection of sitting birds on electrical wire. (a) Original image with varying background and foreground objects. (b) Reconstructed image with circular regions removed. (c) Difference image between original and reconstructed. (d) Segmented objects.

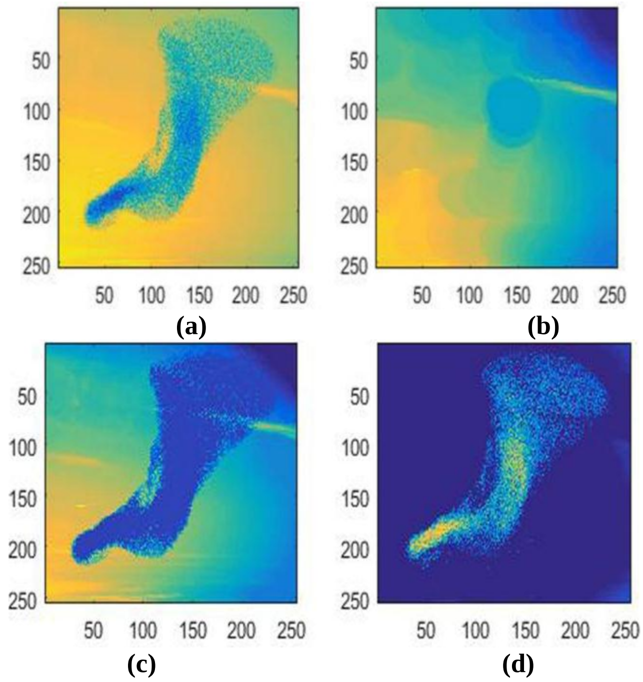

Figure. 5: Detection of migrate birds (a)image with varying background and foreground objects. (b) Reconstructed image with circular regions removed. (c) Difference image between original and reconstructed. (d) Segmented objects.

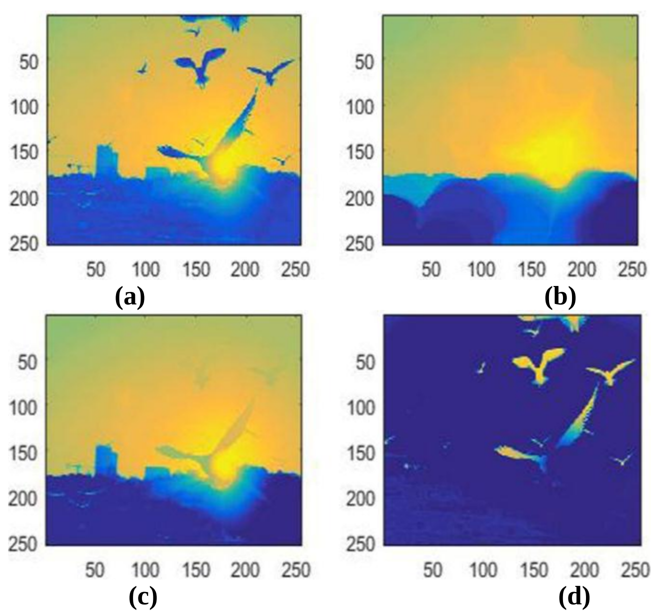

Figure. 6: Detection of flying birds during sunset time. (a) Original image with varying background and foreground objects. (b) Reconstructed image with circular regions removed. (c) Difference image between original and reconstructed. (d) Segmented objects.

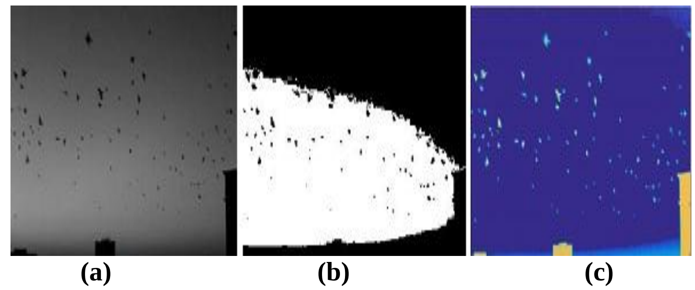

Fig. 7: Comparison between proposed and Otsu's methods (a) Original image (b) Global image threshold using Otsu's method (c) proposed method.

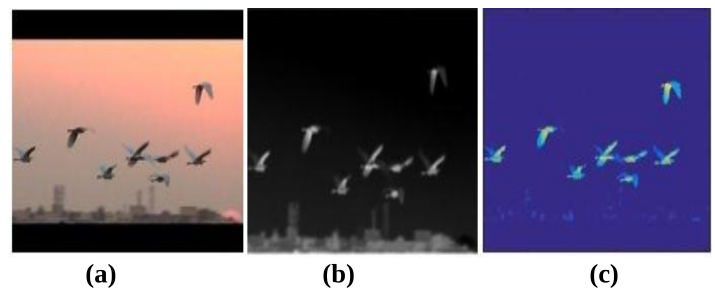

Fig. 8: Comparison between proposed and frequently-tuned methods (a) Original image (b) frequently-tuned method (c) proposed method.

V. Conclusion

This work presented a segmentation of salient object in complex scene of sky images using morphological reconstruction techniques which is detection of regional maximal and reconstruct with use of connectivity. The proposed method segments the salient flying object in complex sky background images in different lighting variation condition like sunset, sunrise and sunshine problem. This method gives effective result for all lighting variation condition without background noises. Experiment on video image data sets demonstrate that the proposed method performs well against existing methods.

References

[1] A. Borji, M.M Cheng and H. Jiang, J. Li, "Salient object detection", A benchmark, IEEE Transactions on Image Processing, 24(12), pp. 5706-5722, 2015.

[2] A. K Mishra, Y. Aloimonos and L.F Cheong, A. Kassim. "Active visual segmentation", IEEE transactions on pattern analysis and machine intelligence, 34(4), 639-653, 2012.

[3] A. Takeki, T.T Trinh and R. Yoshihashi, R. Kawakami, M. Iida and T. Naemura, "Detection of small birds in large images by combining a deep detector with semantic segmentation", In Image Processing (ICIP), IEEE International Conference, pp. 3977-3981, 2016.

[4] A. Toet, "Computational versus psychophysical bottom-up image saliency: A comparative evaluation study", IEEE transactions on

pattern analysis and machine intelligence, 33(11), pp. 2131-2146, 2011.
[5] B. Irving, P. Taylor and A. Todd-Pokropek, "3D segmentation of the airway tree using a morphology-based method.", In Proc. of Second International Workshop on Pulmonary Image Analysis, pp. 297-307, 2009.
[6] C. Pisupati, L. Wolff and E. Zerhouni, W. Mitzner, "Segmentation of 3D pulmonary trees using mathematical morphology", In Mathematical morphology and its applications to image and signal processing, pp. 409-416, 1996.
[7] D. Aykac, E.A Hoffman and G. McLennan, J.M Reinhardt, "Segmentation and analysis of the human airway tree from three-dimensional X-ray CT images", IEEE transactions on medical imaging, 22(8), pp. 940-950, 2003.
[8] J. Kim, D. Han and Y.W Tai, "Salient region detection via high-dimensional color transform and local spatial support", IEEE transactions on image processing, 25(1), pp. 9-23, 2016.
[9] L. Vincent, "Morphological grayscale reconstruction in image analysis applications and efficient algorithms", IEEE transactions on image processing, 2(2), pp. 176-201, 1993.
[10] L. Vincent, "Morphological grayscale reconstruction: definition, efficient algorithm and applications in image analysis", In Computer Vision and Pattern Recognition, Proceedings CVPR, 1992, Computer Society Conference on IEEE, pp. 633-635, 1992.
[11] L. Wang, J. Xue and N. Zheng, G. Hua, "Automatic salient object extraction with contextual cue", In Computer Vision (ICCV), 2011 IEEE International Conference on 2011 Nov, pp. 105-112, 2011.
[12] M. Suresh, Sandeep and T. Harisha Naik, "Recognition of salient bird objects using feed forward back propagation neural networks", Indian Journal of Computer Engineering and Application, Vol. 06. Issue.07, pp. 1-13, 2018.
[13] M.M Cheng, N.J Mitra and X. Huang, P.H Torr, S.M Hu, "Global contrast based salient region detection", IEEE Transactions on Pattern Analysis and Machine Intelligence, 37(3), pp. 569-582, 2015.
[14] N.C Truong Hai, & H.R Park, "Extracting detected salient object by active segmentation", In Proceedings of the 5th International Conference on Ubiquitous Information Management and Communication, pp. 35, 2011.
[15] R. Achanta, S. Hemami and F. Estrada, S. Susstrunk, "Frequency-tuned salient region detection", International Computer vision and pattern recognition(cvpr), 2009, pp. 1597-1604,2009.
[16] W. Qi, M.M Cheng and A. Borji, H Lu, L.F Bai, "Saliency Rank: Two-stage manifold ranking for salient object detection", Computational Visual Media, 1(4), 309-320, 2015.
[17] W. Wang, J. Shen and L. Shao, "Video salient object detection via fully convolutional networks", IEEE Transactions on Image Processing, 27(1), pp. 38-49, 2017.
[18] Y. Li, X. Hou, and C. Koch, J.M Rehg, A.L Yuille, "The secrets of salient object segmentation", Georgia Institute of Technology, 2014.
[19] https://unsplash.com/search/photos/flying-bird.

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