A GROUND TRUTH ANNOTATED VIDEO DATASET FOR MOVING OBJECT DETECTION IN DEGRADED ATMOSPHERIC OUTDOOR SCENES

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ABSTRACT

Moving object detection has been extensively studied during the last few decades. However the detection of moving objects in different degraded atmospheric conditions (i.e. fog, haze, dust and poor illumination) is less understood. This is possibly because of the lack of a suitable and publically-available video dataset under such weather conditions within which salient objects are unambiguously defined and annotated. This paper describes the creation and design of a new video dataset named as "Tripura University Video dataset (TUVD)" which specifically addresses degraded atmospheric weather conditions for moving object detection in outdoor scenes. The objective is to provide video dataset containing moving objects with annotated ground truth in the form of images of the salient objects in the image sequences. Currently, TUVD contains 55 videos of moving objects (vehicles, animals and pedestrian) under degraded atmospheric conditions. Using TUVD a comparison is made between the results of seven existing state-of-the-art visibility enhancement methods. Quantitative assessment of image quality is achieved using four no-reference image based quality assessment metrics. Overall, the most efficient method for visibility restoration of outdoor scenes is found to be one based on multi-scale fusion, although most of the other algorithms tested show interesting capability in specific cases.

Index Terms—Moving Object Detection; Atmospheric Condition; Tripura University Video Dataset (TUVD); Ground truth; Image Enhancement.

1. INTRODUCTION

Moving object detection from outdoor scenes is a fundamental low level task in many computer vision applications including visual surveillance, smart environments and content retrieval. Detection of moving objects is connected with higher level inference tasks such as object localization, tracking, and classification and is often considered as the pre-processing step. A large number of algorithms for moving object detection have been developed but no algorithm has been reported that cope with challenges of outdoor scenes such as sudden illumination variations, background movements, shadows and photometric similarity [1]. The rapid development of complex object detection algorithms originates from the available of benchmark datasets that provides a balanced coverage of the range of challenges representative of the real world [2]. In the last few decades, large datasets are designed to meet the increasing demands in developing and benchmarking new models for object detection [2]-[15]. A summary of publically available object detection datasets is given in Table 1. Each of these datasets are extensive in terms of amount or complexity. However, there is still a lack of video datasets for moving object detection that can provide a balanced coverage in weather/atmosphere degraded outdoor scenes. Generally North-Eastern (NE) state and other states of India share multiple international borders and border security is vital. In extreme atmospheric conditions such as fog, haze, dust, and rain, suspicious intruders may not be detected by unaided human vision due to a high loss in contrast. Consequently electronic surveillance has an important role to play in detecting illegal threats to the state and for real time detection of suspicious activities.

Recognizing the importance of moving object detection to the computer vision and video processing communities, the primary contributions of this paper are summarized below:

1. The paper provides the research community with a comprehensive "Tripura University Video Dataset (TUVD)" of outdoor scenes degraded by different atmospheric conditions (i.e. fog, dust and poor illumination) for moving object detection so that one can utilize this dataset for testing and ranking of existing and new algorithms for moving object detection in degraded atmospheric conditions.
2. The paper provides a procedure for generating the ground truth images of the suspected salient objects in each of the extracted frames of the created video dataset.
3. The paper also provides a comparison of seven most widely used state-of-the-art visibility enhancement methods based on no-reference image based quality assessment metrics and thus, helps to select the most effective enhancement methods for restoring the weather degraded outdoor scenes and help to identify the remaining challenges in order to provide focus for future research.

The paper is organized as follows: Section 2 describes the design issues and statistics of TUVD under different atmospheric conditions. In Section 3, the generation of ground truth images of the salient moving objects in each of the extracted frames is described. In Section 4, seven popular and widely used state-of-the-art visibility enhancement techniques are implemented for restoration of weather degraded extracted frames and reports the experimental results of these methods on our TUVD dataset. And finally, Section 5 concludes the paper.

2. DESIGNING ISSUES AND OVERALL STATISTICS OF CREATED TRIPURA UNIVERSITY VIDEO DATASET (TUVD)

Generally the appearance of scene alters depending on several factors such as geometrical view, scene construction, illumination and weather conditions. In order to develop and test a complex algorithm for detecting moving objects in extreme weather degraded conditions, a standard video dataset is needed that cover many real-world scenarios. In this section

Table 1: Review on Existing Object Detection Dataset Used in Research Work

Frame/ Video Based Object Detection Dataset

Name of the Dataset	Key Characteristics	No. of videos/ Scenes	Dataset Details				Total No. of Frames	Ground Truth Frames
			Environment Condition	Image Format	Dataset Type	Pixel Resolution		
CD.net 2012 [2]	Camera Jitter, Dynamic Background, Intermittent Object Motion, Shadow	31	Indoor and Outdoor	.jpg	V/T/C	320×240 to 720×480	99150	68126 (PBL)
BMC2012 [3]	Complex Background, Climatic conditions, Shadow, Crowded	20	Outdoor	.png	V/C	640×480	29980	15980 (PBL)
PETS2009 [4]	Illumination change, Crowded, Shadow	8	Outdoor	.avi	V/C	720×576 to 768×576	NP	NP (BB)
I2R [5]	Dynamic Background, Bootstrapping, Illumination Change	9	Indoor and Outdoor	.jpg	V/C	176×144	37958	37958 (PBL)
ETISEO [6]	Crowded, Occlusion and Shadow, Illumination change	118	Indoor and Outdoor	.mov	V/T/C	640×480	153243	153243 (BB, OC)
DAVIS [7]	Cluttered Background, Motion Blur, Occlusion, Camera shake, Interacting objects	50	Outdoor	.jpg	V/C	1920×1080	3455	3455 (PBL)
Wallflower [8]	Illumination change, Background motion, Camouflage Foreground Object, Bootstrapping	7	Indoor and Outdoor	.bmp	V/C	640×480	NP	7 (PBL) i.e. 1 Frame Per video
ViSal [9]	Dynamic texture, Crowded, Interacting objects, Pose Variation	17	Indoor and Outdoor	.jpg	V/C/G	512×288	963	193 (PBL)
SegTrack [10]	Motion blur, Appearance change, Complex deformation, Occlusion, Interacting objects	6	Outdoor	.png	V/C	320×240 to 414×352	244	244 (PBL)
SegTrack V2 [11]	Motion blur, Appearance change, Complex deformation, Occlusion, Interacting objects	14	Outdoor	.png	V/C	259×327 to 640×360	976	976 (PBL)
FBMS [12]	Occlusion, Illumination Change, Background motion	59	Indoor and Outdoor	.jpg	V/C	960×540	13860	720
VOS [13]	Complexity of foreground, Background motion	200	Indoor and Outdoor	.mov	V/C	800×800	116103	7467 (PBL)
Fish4Knowledge [14]	Blurred, Complex background, Luminosity Change, Camouflage Foreground Object, Crowded, Hybrid of all above	14	Underwater	.avi	V/C	320×240	NP	3500 (PBL) i.e. 250 Frame Per video
BMC2012 [3]	Complex Background, Climatic conditions, Shadow, Crowded	9	Outdoor	.avi	V/C	320×240	NP	586 (PBL)
MAR [15]	Complex Background, Blur, Haze, Occlusion	27	Outdoor	.mp4	V/C	352×288 to 1676×576	NP	NP

PBL- Pixel Based Labeling, BB- Bounding Box, OC- Object Class, V- Visual, T-Thermal, C-Color, G- Gray, NP- Not Provided

the design issues, overall statistics and naming conventions of TUVD are described.

2.1. Image Capturing Conditions and Acquisition Set up

The images in outdoor environment are mainly influenced by two factors: Weather and Illumination [16]. Such conditions alter the key characteristics (i.e. intensity, color, polarization, coherence) of sunlight due to scattering by atmospheric particles [16]. The atmospheric conditions considered in this study are Foggy Condition, Dust condition, Poor Illumination Condition and Clear Day.

A great deal of effort has been done on measuring the physical properties of these atmospheric conditions [16]. It has been observed that poor visibility occurs when the difference between normal temperature and dew point is less than 2.5°C and visibility remains less than 1 KM [17]. Based on these observations, several factors which are considered during data acquisition so as to reduce the negative influence of analysis is shown in Fig. 1. Some of the sample frames of Tripura University Video Dataset (TUVD) in different atmospheric conditions are shown in Fig. 2.

2.2. Dataset Statistics

By maintaining the above mentioned acquisition factors, currently TUVD contains 55 videos under different atmospheric conditions (as shown in Fig. 2). Each video clip has a duration of 2 minutes (3600 frames per video) with a frame rate of 30 fps (Frame Per Second). The overall statistics of the created dataset is shown in Table 2. The main features of the TUVD are as follows:

- **Background Challenges:** The dataset are captured under two background conditions (i.e. static and dynamic background). For capturing the video with a static background, the camera is kept fixed with respect to the moving objects i.e. the background is static with respect to the moving objects. Conversely for dynamic background, the video is captured by mounting the camera on a moving vehicle (20~30 km/h) [18] where both the objects and

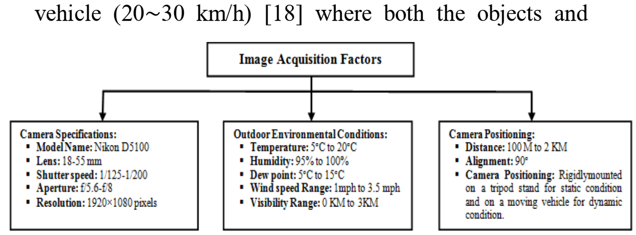

Fig. 1 Camera Setup and Acquisition Factors of TUVD

Table 2: Distribution of Tripura University Video Dataset (TUVD) in Atmospheric Conditions

Image Type	Camera Model	Background Condition	Atmospheric Conditions				Total Videos
			Clear Day	Poor Illumination	Foggy Condition	Dust Condition	
Visual	Nikon D5100	Static	4	6	16	11	37
		Dynamic	3	3	7	5	18
Total Number of Videos			**7**	**9**	**23**	**16**	**55**

**As on 29th December, 2017(dataset is still growing)

Table 3: Codes Used for Naming the TUVD

Atmospheric Condition		Background Condition		Capturing Day	
Mode	**Codes**	**Type**	**Codes**	**Day**	**Codes**
Foggy	F	Static	S	Day1	D1
Dust	D	Dynamic	D	Day2	D2
Poor Illumination	PI			...	...
Clear Day	CD			Dayn	Dn

background are moving simultaneously.

- **Atmospheric Challenges:** The dataset includes urban scenes with buildings, trees, sky, vehicles and pedestrian with range from about 100 meters to about 5 kilometer so as to facilitate the observation of atmospheric effects (i.e. poor illumination, foggy weather condition and dust condition) on scene appearances.
- **Other Challenges:** Beside these two major challenges, the dataset also contains scenes with multiple moving objects in single frame, overlapping of two moving objects in particular frame, camouflage or poorly textured moving objects and intermittent motions of objects.

This subsets is very challenging and can be used to test benchmark algorithms in realistic scenarios.

2.3. Naming Convention

Naming of the Tripura University Video Dataset (TUVD) has been done for the ease of understanding the category of the dataset during analysis. Different codes are assigned for different atmospheric condition, different date on which data is captured and also for the type of background. All the assigned codes for each component of the name are illustrated in Table 3. With all these codes, the name of a dataset is like **Capturing-Day_Atmospheric-Condition_ Background-Type_Video-ID.mov**. Based on the codes provided in Table 3, the video name "**D1_F_S_01.mov**", indicates that the video is with Video_ID 01 is static background video captured under foggy condition on the first day.

3. GROUND TRUTH GENERATION OF SALIENT MOVING OBJECTS ON TRIPURA UNIVERSITY VIDEO DATASET (TUVD)

Ground truth generation of salient moving objects allows understanding the efficiency of object detection and tracking algorithms. However manual annotation of an accurate ground truth data which contains moving objects often results in uncertainty and strongly subjective bias. Based on the work of Y. Li et.al. [19], we collected two types of ground truth data,

Fig. 3 Sample Video Frame from the Dataset and Corresponding Ground-truth label fields (a) Original Frame; (b) Rectangular Box Bounding Moving Object; (c) Corresponding Moving Object Mask

object fixation using rectangular bounding boxes and object masks. The procedure is described in detail below.

3.1. Rectangular Box based Moving Object Fixation

Currently the dataset contains 55 videos each of 2 minutes (3600 frames per video). So it is very difficult for a person to generate accurate binary ground truth images of moving objects (i.e. object masks) for captured videos. Ideally the moving objects in each of the extracted frames should be labelled in the form of rectangular box so as to reduce the unambiguousness while generating the object masks. To implement the protocol five members of the research laboratory who are working in the respective domain as their post graduate projects, are selected. Each of these five workers are given these four categories of videos for annotating the videos with appropriate rectangular boxes. Each worker is asked to free-view all the extracted frames of the videos distributed to them and to fix the two coordinate points defining the width and height of the bounding box i.e. upper most left corners and lower most right corners and based on this two points other two points are fixed i.e. upper most right corners and lower most left corners. Finally using these coordinate locations, rectangular boxes are drawn using MATLAB R2013b software bounding each of the moving objects present in the scene.

3.2. Generation of Object Masks

Generation of uncontroversial binary ground-truth images of moving objects for captured videos is very difficult and challenging task. Considering all these factors, one of the most well-known software tools i.e. GNU Image Manipulation Program Tool [20] is used for generation of the binary masks for moving objects from each frames. Five

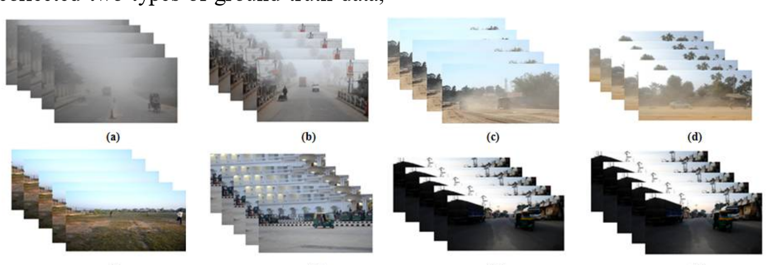

Fig. 2 Sample Image Frames of Tripura University Video Dataset (TUVD) in Different Atmospheric Conditions (a), (b) Foggy condition; (c), (d) Dust Condition; (e), (f) Clear Day; (g), (h) Poor Illumination

workers were selected who have not participated in annotating the bounding boxes of moving. Similarly distributing the dataset as described in the previous subsection, ground-truth images are produced with the following two labels: Assigned grayscale value of 0 if it is a static pixel and assigned grayscale value of 255 if it is a moving pixel. Fig.3. (b) and (c) shows the example of bounding box fixation and generation of corresponding binary object mask in our created dataset respectively.

4. QUALITATIVE COMPARISON OF IMAGE SEQUENCES ENHANCED BY USING THE STATE-OF-THE ART VISIBILITY RESTORATION METHODS

4.1. Visibility Enhancement

Scattering of light by turbid medium has been one of the major research topics in the domain of atmospheric optics and astronomy communities [21]. Numerous computer aided visibility enhancement techniques have been proposed in the literature for restoration of weather degraded images. The comprehensive description of various representative methods in each of this category has been reported in our previous work [22]. Based on the rigorous study, it is found that the visibility enhancement methods like Fusion based strategy [23], Filtering based strategy [24], Dark channel strategy [25], Structure-Texture decomposition based strategy [26], Bayesian probabilistic strategy [27], Boundary constraint based strategy [28] and Stochastic enhancement strategy [29] are the most simple and efficient well known techniques used by most researchers as standard techniques for their study. So in our work we have used these seven enhancement methods for comparative study.

4.2. No-Reference Image based Quality Analysis

This subsection evaluates the state-of-the-art methods for visibility restoration of weather degraded image sequences. Since none of visibility enhancement methods are applicable to all images and also are not equally suitable for all the weather conditions, the qualitative assessment of these techniques is indispensable. In our work, the difference and efficiency of these methods is carried out in terms of four non-reference qualitative assessment methods and execution time. The four non-reference image based qualitative assessment metrics are [30][31]: Rate of new visible edges (e), Mean ratio (σ), Percentage of pixels (r) and Local Block Based FISH (LBBFISH). A higher value of e, r and LBBFISH and lower value of σ means a better enhanced image.

For qualitative evaluation, three videos from each of the weather conditions (i.e. fog and dust) are selected from TUVD. According to the extraction rules, 300 frames are selected (i.e. from 3600 frames per video, 1 frame is selected per 10 frames) from each of these videos for analysis. The average value of these qualitative assessment metrics for restoring the visibility of weather degraded image sequences are shown in Table 4. For evaluation of computational time, each of these methods are tested on a workstation with specification of Intel Core i5 CPU with 8 GB RAM. The size of each images are resized to 500×500 pixels.

From this comparative analysis, it is found that although the enhancement techniques as proposed by [28] needs less time to process all the images of TUVD but regarding qualitative comparison these method underperforms and is not effective to restore the visibility of the scene. Conversely, method proposed by [23] and [29] outperforms the remaining five methods both qualitatively and quantitatively. It is clear from Table 4 that after visibility enhancement, objects and other scenes in outdoor scenes are more visible and can be used as a pre-processing step before applying algorithms for accurate detection of moving objects in outdoor atmospheric degraded scenes.

5. CONCLUSION

We have presented a ground truth annotated video dataset namely as Tripura University Video Dataset (TUVD) for moving object detection in degradation atmospheric outdoor scenes. The dataset aims to provide the research community with a facility for testing and ranking of existing and new algorithms for moving object detection in outdoor environment. Furthermore, the paper investigates the potentiality of the some well-known visibility enhancement techniques based on no-reference image based quality assessment metrics. The evaluation metrics demonstrates that although the enhancement techniques are efficient for restoration of fog degraded outdoor scenes but success has still been limited for dust condition. In future the dataset will be regularly revised and extended to include other atmospheric conditions. Also we will rank the prominent object detection algorithms in the various categories and will develop new detection algorithm to overcome the limitations of the state-of-the-art methods.

Table 4: No-Reference Image Based Qualitative Evaluation and Computational Time of The State-of-the-Art Visibility Enhancement Methods on Tripura University Video Dataset (TUVD)

Author	Scene	Qualitative Assessment and Computational Time of Weather Conditions									
		Foggy Condition					Dust Condition				
		e	σ	r	LBBFISH	CT	e	σ	r	LBBFISH	CT
Ancuti et.al. [23]	Scene 1	**0.9391**	**0.0002**	**4.9008**	**21.5759**	**4.6387**	**0.6234**	**0.0543**	**1.0973**	**15.6745**	**12.4381**
	Scene 2	**0.8259**	**0.0004**	**3.0004**	**19.9543**	**5.5432**	**0.5559**	**0.0469**	**1.1256**	**13.1345**	**11.2395**
	Scene 3	**0.9092**	**0.0011**	**4.8354**	**21.0567**	**4.0982**	**0.7653**	**0.0598**	**1.1103**	**17.3786**	**11.2453**
Tarel et.al. [24]	Scene 1	0.5923	0.0398	2.7197	17.7585	22.8968	0.2356	0.0785	0.9623	10.5634	43.7641
	Scene 2	0.5341	0.0231	2.3452	19.9543	24.5436	0.3425	0.0723	0.9268	12.3452	45.8752
	Scene 3	0.6342	0.0087	2.8735	18.3654	21.4387	0.2679	0.0701	0.7356	11.5645	44.7975
He et.al. [25]	Scene 1	0.8713	0.0021	2.8833	20.5605	21.3738	0.5464	0.0132	0.7865	12.1654	40.3754
	Scene 2	0.8112	0.0100	2.0972	19.6736	31.0842	0.4996	0.0135	0.7534	10.5601	37.8459
	Scene 3	0.7545	0.0017	2.0045	15.4211	25.5477	0.5053	0.0154	0.7200	11.2314	37.0003
Li et.al. [26]	Scene 1	0.6784	0.0029	2.9209	19.8132	43.1457	0.3588	0.0134	0.7321	10.5673	59.0860
	Scene 2	0.5123	0.0010	2.8753	23.5641	42.8743	0.3986	0.0198	0.7543	12.3456	52.0014
	Scene 3	0.7452	0.0027	2.4526	15.6782	44.6742	0.3767	0.0178	0.6787	14.3342	54.5795
Nishino et al. [27]	Scene 1	0.5144	0.0089	1.7446	17.4721	47.4830	0.5563	0.0234	0.4309	12.0001	59.0674
	Scene 2	0.7323	0.0090	1.9871	21.5670	44.5443	0.4546	0.0245	0.4897	12.3452	54.6750
	Scene 3	0.7543	0.0200	1.5756	16.7632	45.3245	0.5498	0.0241	0.4371	12.2345	56.0957
Meng et.al. [28]	Scene 1	0.3842	0.0484	1.6727	16.8261	**11.5716**	0.0256	0.0256	0.9342	11.1002	**17.5695**
	Scene 2	0.2312	0.0035	2.1042	17.5372	**8.9864**	0.0197	0.0174	0.8453	12.1453	**20.0001**
	Scene 3	0.3343	0.0156	2.5673	17.0004	**12.2120**	0.0262	0.0239	0.8045	10.0523	**20.5853**
Bhattacharya et.al [29]	Scene 1	**0.9078**	**0.0005**	**4.6621**	**22.0799**	13.3503	**0.6974**	**0.0456**	**1.1297**	**18.2345**	23.6549
	Scene 2	**0.9192**	**0.0017**	**3.0201**	**22.2676**	21.5621	**0.6053**	**0.0593**	**1.2347**	**18.0734**	23.0045
	Scene 3	**0.8879**	**0.0008**	**4.4356**	**19.9873**	17.4372	**0.6632**	**0.0598**	**1.0976**	**18.5564**	21.9453

**CT: Computational Time in Seconds

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