Advances in Intelligent Systems and Computing 703

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Proceedings of 2nd International Conference on Computer Vision & Image Processing

CVIP 2017, Volume 1

Springer

Advances in Intelligent Systems and Computing

Volume 703

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ISSN 2194-5357 ISSN 2194-5365 (electronic)
Advances in Intelligent Systems and Computing
ISBN 978-981-10-7894-1 ISBN 978-981-10-7895-8 (eBook)
https://doi.org/10.1007/978-981-10-7895-8

Library of Congress Control Number: 2017963008

Printed on acid-free paper

This Springer imprint is published by Springer Nature
The registered company is Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Preface

The Second International Conference on Computer Vision and Image Processing (CVIP 2017) was organized at Indian Institute of Technology Roorkee (IITR), Greater Noida Extension Center, during September 09–12, 2017. The conference was endorsed by International Association of Pattern Recognition (IAPR) and was primarily sponsored by MathWorks. CVIP 2017 brought together delegates from around the globe in the focused area of computer vision and image processing, facilitating exchange of ideas and initiation of collaborations. Among 175 paper submissions, 64 (37%) were accepted based on multiple high-quality reviews provided by the members of our technical program committee from ten different countries. We, the organizers of the conference, were ably guided by its advisory committee comprising distinguished researchers in the field of computer vision and image processing from seven different countries. A rich and diverse technical program was designed for CVIP 2017 comprising five plenary talks and paper presentations in seven oral and two poster sessions. Emphasis was given to the latest advances in Cybernetic Health, Perception of Visual Sentiment, Reshaping of Human Figures in Images and Videos Using 3D Morphable Models, Vision and Language, and Challenges in Biometric System Development. The papers for the technical sessions were divided based on their theme relating to Computer Vision Applications, Document Image Analysis, Machine Learning and Uncertainty Handling, Surveillance and Security, Summarization, Retrieval and Recognition, and Low-level Computer Vision. This edited volume contains the papers presented in the technical sessions of the conference, organized session-wise. Organizing CVIP 2017, which culminates with the compilation of the volume of proceedings, has been a gratifying and enjoyable experience for us. The success of the conference was due to synergistic contributions of various individuals and groups including the international advisory committee members with their invaluable suggestions, the technical program committee members with their timely high-quality reviews, the keynote speakers with informative lectures, the local organizing committee members with their unconditional help, and our sponsors and endorsers with their timely support. Finally, we would like to thank Springer for agreeing to publish the proceedings in their prestigious Advances in Intelligent Systems and Computing (AISC) series. We hope the technical contributions made by the authors in these volumes presenting the proceedings of CVIP 2017 will be appreciated by one and all.

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Moving Target Detection Under Turbulence Degraded Visible and Infrared Image Sequences

Chaudhary Veenu, Kumar Ajay and Sharma Anurekha

Abstract The presence of atmospheric turbulence over horizontal imaging paths introduces time-varying perturbations and blur in the scene that severely degrade the performance of moving object detection and tracking systems of vision applications. This paper proposed a simple and efficient algorithm for moving target detection under turbulent media, based on adaptive background subtraction approach with different types of background models followed by adaptive global thresholding to detect foreground. This proposed method is implemented in MATLAB and tested on turbulence degraded video sequences. Further, this proposed method is also compared with state-of-the-art method published in the literature. The result shows that the detection performance by proposed algorithm is better. Further, the proposed method can be easily implemented in FPGA-based hardware.

Keywords Moving object detection · Imaging under turbulent media Performance metrics · Background subtraction · Computer vision and target detection algorithm

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B. B. Chaudhuri et al. (eds.), *Proceedings of 2nd International Conference on Computer Vision & Image Processing*, Advances in Intelligent Systems and Computing 703, https://doi.org/10.1007/978-981-10-7895-8_1

1 Introduction

Robust and automatic target detection is an important application in computer vision systems and its performance is severely limited, particularly at longer ranges, due to atmospheric degradation such as atmospheric turbulence. Atmospheric turbulence is random, nonlinear, and optical phenomenon that limits the viewing through any atmospheric path, e.g., twinkling of stars, distant lights, shimmering of objects on hot sunny day. These effects are caused due to local reflections and refractions by atmosphere which varies with time, resulting variation in the refractive index [1]. This nonuniform and continuous variation in refractive index results variation of phase of the received optical wave front. These variations in the received distorted wave front cause the image to be focussed at different points in the focal plane of the receiving optics, causing turbulence distortions. This turbulence causes the light from target scene to reach the imaging system with perturbations, i.e., spatiotemporal fluctuations [2].

In general, turbulent medium results target scene in the video sequences to appear blurry and wavering that renders movements in scene even when objects of the scene is stationary. These turbulence-induced movements in the target scene have characteristics that might be similar to those of the real moving objects, resulting significant increase in false detection, thereby degrading the detection performance of the machine vision system. Therefore, it becomes necessary to identify real moving objects in target scene from dynamic background.

Several methods for moving object detection in video sequences have been reported in the literature, but only few dealt with atmospheric turbulence-induced movements [2–8]. Direct background–foreground segmentation methods such as frame differencing [3] and Gaussian mixture model [6] do not perform well in turbulent scenarios, as motions induced by turbulence cause a lot of false detection. Fishbain et al. [2] proposed a method to preserve object motion while eliminating turbulence in real time. In their approach, a reference background image is computed using a temporal median filter. Then, displacement map of individual frames from reference background frame is estimated. Displacement map is then segmented to detect stationary and moving objects. Turbulence compensation is done while preserving moving objects. Oreifej et al. [5] proposed a method to simultaneously recover the stable background and moving objects. The method includes a three-term low rank matrix decomposition approach, with components-background, turbulence-induced motion, and real moving objects. However, this method is computationally very intensive and has high computation and memory requirements. Baldini et al. [7] proposed a method for moving target tracking in dynamic background condition. In their approach, probabilistic method for motion detection is chosen and each detected blob is tracked by matching them with those found by block matching technique. A true object was declared after being tracked for at least three frames. The algorithm has been tested on image sequences of different weather conditions. This method is also highly computationally intensive. Barnich et al. [9] proposed a universal background subtraction algorithm for motion detection that is based on pixel-by-pixel comparison in order to determine whether that pixel belongs to the background and adapts the model. Eli Chen et al. [8] proposed a method based on novel criteria for objects' spatiotemporal properties, to discriminate true objects from false detections, using pixel-based adaptive thresholding technique for foreground detection.

In the present paper, a simple and efficient algorithm is proposed for real moving target detection in turbulence degraded visible and infrared image sequences. The proposed algorithm increases detection performance by increasing true detection and reducing false negative rates significantly. In this paper, the proposed moving target detection method is based on the combination of two types of adaptive background subtraction techniques followed by foreground extraction with adaptive global thresholding. We have tested the proposed method on various video sequences degraded by atmospheric turbulence. The performance analyses of the proposed algorithm were carried out by implementing it in MATLAB (R2012a). Further, this method is also compared with various other reported object detection methods by testing it on various atmospheric degraded image sequences (available at online resources [10]) taken at varying degree of turbulence. Results obtained the performance analysis parameters establishes that the proposed method performs better for moving target detection in turbulence degraded image sequences.

The remainder of this paper is organized as follows: Sect. 2 describes the evolved method and block diagram of the proposed algorithm for moving target detection under turbulence medium. Sections 3 and 4 discuss the proposed performance metrics for results and comparison with state-of-the-art method reported in [8]. Section 5 concludes this paper along with future work.

2 Proposed Algorithm

Background subtraction technique is used to identify moving objects in video frames [11]. A large set of algorithms, reviewed in [12], have been designed to segment the foreground objects from the background of the sequence. The background subtraction methods presented in [12] are based on single method and hierarchy method approaches. However, in the proposed approach for moving target detection under turbulence, we present simultaneously two methods and combine their results to improve the target detection probability and deductions of false alarms.

In the proposed method, each frame of the input video is subtracting from a background image to identify moving pixels. Background image is computed based upon the adaptive background models and is updated in every frame. For turbulence degraded image sequence, background model should be adaptive in nature. This proposed method combines background subtraction techniques based on adaptive background model and temporal mean (moving average) filter background model. The foreground regions are calculated by applying adaptive global thresholding on each absolute background subtraction.

Let $I_n(x, y)$ is the current image frame and **(x, y)** is the image coordinates. We define the following two models for estimating background:

The first estimated background model is

$$B_n^{\mathbf{1}}(x, y) = \boldsymbol{\alpha} B_{n-\mathbf{1}}(x, y) + (1 - \boldsymbol{\alpha}) I_n(x, y) \tag{1}$$

where $B_n^{\mathbf{1}}(x, y)$ is the first estimated background at nth frame and $\boldsymbol{\alpha}$ is the background learning parameter whose value lies between 0 and 1. Its value is taken to be 0.7 in the proposed method for estimating $B_n^{\mathbf{1}}(x, y)$.

We defined the second estimated background model as:

$$B_n^{\mathbf{2}}(x, y) = mean(I_t(x, y)) \tag{2}$$

where $t = n + \mathbf{1}, \mathbf{n} + \mathbf{2}, \ldots \mathbf{n} + \mathbf{N}$ and $B_n^{\mathbf{2}}(x, y)$ is second estimated background which is based on moving average filter with window size N = 15 at nth frame.

The background subtracted images of background models $B_n^{\mathbf{1}}(x, y)$ and $B_n^{\mathbf{2}}(x, y)$ are defined as

$$BS_n^{\mathbf{1}}(x, y) = \left| I_n(x, y) - B_n^{\mathbf{1}}(x, y) \right| \tag{3}$$

$$BS_n^{\mathbf{2}}(x, y) = \left| I_n(x, y) - B_n^{\mathbf{2}}(x, y) \right| \tag{4}$$

where $BS_n^{\mathbf{1}}(x, y)$ and $BS_n^{\mathbf{2}}(x, y)$ are two background subtracted images based upon estimated background model 1 and background model 2, respectively.

Adaptive threshold is applied on background subtracted images $BS_n^{\mathbf{1}}(x, y)$ and $BS_n^{\mathbf{2}}(x, y)$ in each frame for detecting moving objects. The threshold value for background subtracted image $BS_n^{\mathbf{1}}(x, y)$ is defined as:

$$th\,low = m(BS_n^{\mathbf{1}}(x, y)) - k_1 * std(BS_n^{\mathbf{1}}(x, y)) \tag{5}$$

$$th\,high = m\left(BS_n^{\mathbf{1}}(x, y)\right) + k_1 * std(BS_n^{\mathbf{1}}(x, y)) \tag{6}$$

$$th\,low \le Th_n^{\mathbf{1}} \le th\,high \tag{7}$$

where $\mathbf{m}(BS_n^{\mathbf{1}}(x, y))$ is the global mean of $BS_n^{1}(x, y)$ image and $\mathbf{std}(BS_n^{\mathbf{1}}(x, y))$ is the standard deviation of $BS_n^{\mathbf{1}}(x, y)$ image. Global mean ($\boldsymbol{m}$) and standard deviation (**std**) on background subtracted image are computed as follows:

$$m = \frac{1}{PXQ} \sum_{x=0}^{P-1} \sum_{y=0}^{Q-1} BS_n^{\mathbf{1}}(x, y) \tag{8}$$

$$std = \frac{1}{PXQ}\sqrt{\sum_{x=0}^{P-1}\sum_{y=0}^{Q-1}\left[BS_n^{\mathbf{1}}(x,y) - m\right]^2} \tag{9}$$

where $\boldsymbol{P}$ and $\boldsymbol{Q}$ are the number of rows and columns of the image, respectively.

In the calculation of threshold value $Th_n^{\mathbf{1}}$, $\boldsymbol{k_1}$ is the bias which can control the adaptation in threshold value and value of $\boldsymbol{k_1}$ is kept at 2.7 in this proposed method.

Threshold value $Th_n^{\mathbf{2}}$ for background subtracted image $BS_n^{\mathbf{2}}(x,y)$ is defined by Otsu's threshold value [13] of estimated background model $B_n^{\mathbf{2}}(x,y)$ given as in [14].

Once the background images are computed, we define the foreground images as:

$$F_n^{\mathbf{1}}(x,y) = \begin{cases} \mathbf{1}, & BS_n^{\mathbf{1}}(x,y) = Th_n^{\mathbf{1}} \\ \mathbf{0}, & \textbf{otherwise} \end{cases} \tag{10}$$

$$F_n^{\mathbf{2}}(x,y) = \begin{cases} \mathbf{1}, & BS_n^{2}(x,y) \geq Th_n^{2} \\ \mathbf{0}, & \textbf{otherwise} \end{cases} \tag{11}$$

where $F_n^{\mathbf{1}}(x,y)$ is the foreground image based on first estimated background subtraction technique that uses background modeling defined as per Eq. (1) and $F_n^{\mathbf{2}}(x,y)$ is the foreground image based on the second background subtraction technique that uses background modeling of Eq. (2).

The detected foreground pixels $F_n^{\mathbf{1}}(x,y)$ and $F_n^{\mathbf{2}}(x,y)$ undergo morphological operation of opening and closing with disk-type structure element $\boldsymbol{SE}$ of order 5×5 [14].

The morphological operation of opening [14] is defined as:

$$A_n^{\mathbf{1}}(x,y) = ((F_n^{\mathbf{1}}(x,y))\,\mathbf{o}\,SE) = (F_n^{\mathbf{1}}(x,y) \ominus SE) \oplus SE \tag{12}$$

where $A_n^{\mathbf{1}}(x,y)$ are the foreground pixels of opening operation on $F_n^{\mathbf{1}}(x,y)$. The holes will be filled in the pixels of $A_n^{\mathbf{1}}(x,y)$ that are smaller than SE by closing operation, dilation following erosion operation, given as:

$$FG_n^{\mathbf{1}}(x,y) = ((A_n^{\mathbf{1}}(x,y) \bullet SE) = (A_n^{\mathbf{1}}(x,y) \oplus SE) \ominus SE \tag{13}$$

where $FG_n^{\mathbf{1}}(x,y)$ is the foreground image produced after morphological operations on first foreground image $F_n^{\mathbf{1}}(x,y)$.

Similarly, morphological operation of opening and closing with disk-type structure element $\boldsymbol{SE}$ of order 5×5 is done on second foreground image $F_n^{\mathbf{2}}(x,y)$ defined by:

$$A_n^{\mathbf{2}}(x,y) = ((F_n^{\mathbf{2}}(x,y))\,\mathbf{o}\,SE) = (F_n^{2}(x,y) \ominus SE) \oplus SE \tag{14}$$

where $A_n^{\mathbf{2}}(x,y)$ are the foreground pixels of opening operation on $F_n^{\mathbf{2}}(x,y)$. The holes will be filled in the foreground image $A_n^{\mathbf{2}}(x,y)$ that are smaller than SE by closing operation, dilation following erosion operation, given as:

$$FG_n^{\mathbf{2}}(x,y) = ((A_n^{\mathbf{2}}(x,y) \bullet SE) = (A_n^{\mathbf{2}}(x,y) \oplus SE) \ominus SE \tag{15}$$

where $FG_n^{\mathbf{2}}(x,y)$ is the foreground image produced after morphological operations on second foreground image $F_n^{\mathbf{2}}(x,y)$.

Next, we perform logical AND operation between foreground images $FG_n^{\mathbf{1}}(x,y)$ and $FG_n^{\mathbf{2}}(x,y)$ to extract moving pixels from the background. Lastly, the connected component algorithm [14] is used for detecting motion regions in blobs and each region is enclosed in bounding box to present moving object in target scene.

Block diagram of the proposed method of moving target detection in turbulence degraded image sequences is given in Fig. 1. In order to implement the proposed algorithm in MATLAB for detection of moving objects in turbulence-induced movements, we have recorded several video sequences under various atmospheric turbulence conditions. Out of these videos, two video sequences were taken. Each video sequence comprises of 110 frames having a resolution of 760 $\times$ 480 pixels. The ground truth of various real moving targets present in these videos is represented as green color bounding boxes where as detected targets after applying the

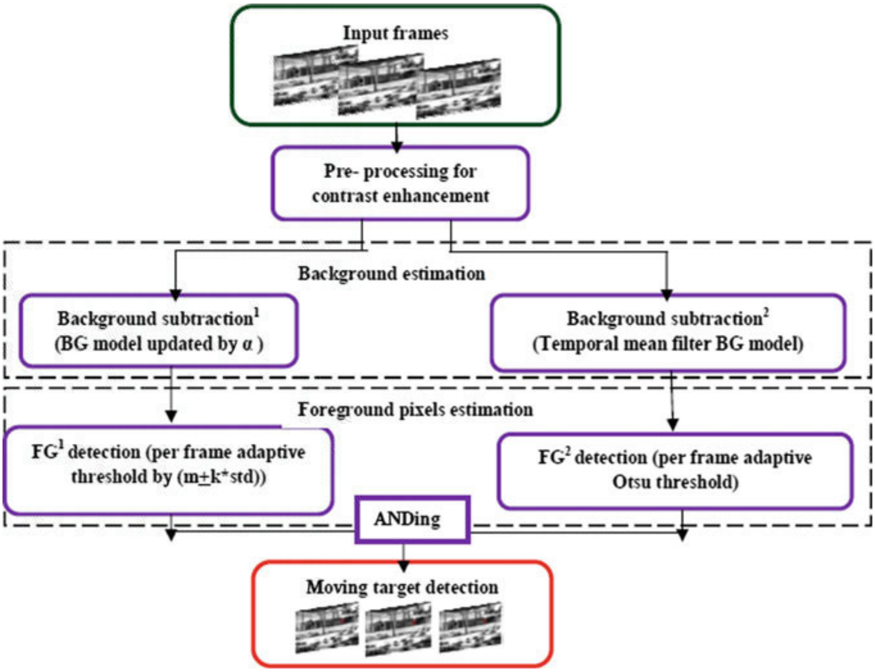

Fig. 1 Block diagram of the proposed method for moving target detection under turbulent media

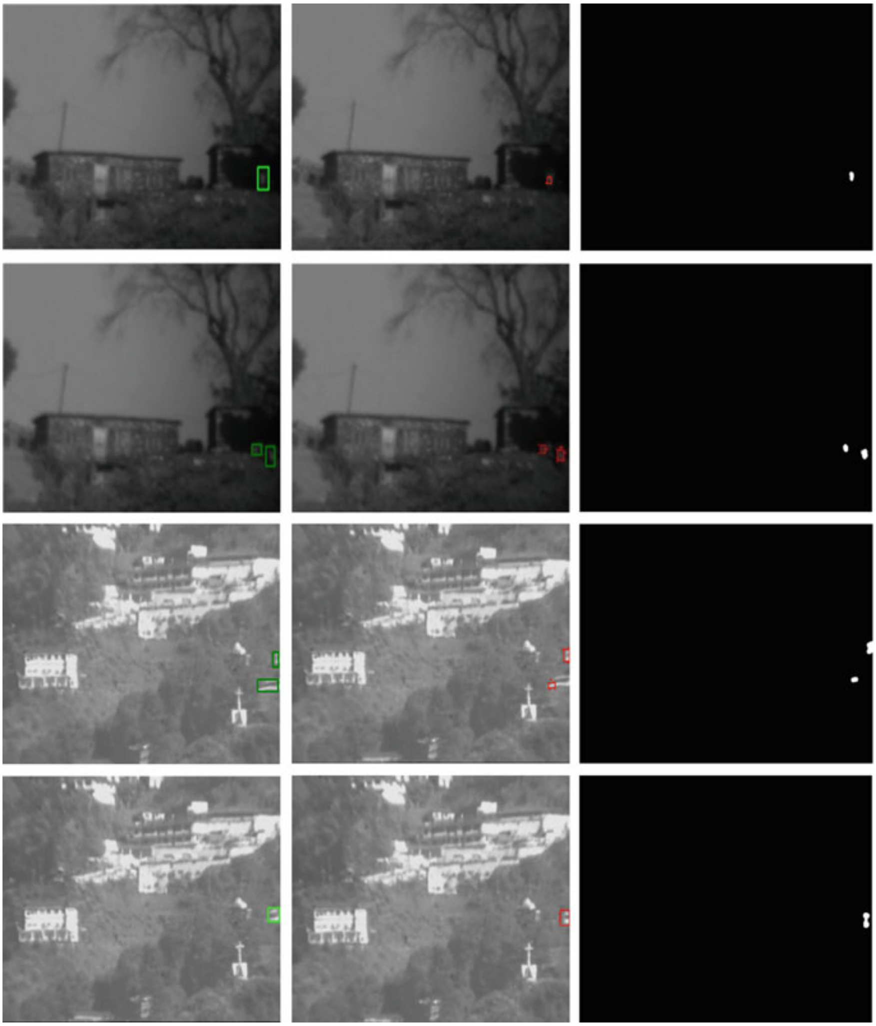

Fig. 2 Sample frames showing ground truth and implementation results of the proposed method on turbulence degraded two video sequences. The first column indicates ground truth information of input frames (green bounding box). Implementation results of the proposed method in column 2 and 3 show detected targets by red bounding boxes and background map, respectively

proposed method is represented as red color bounding boxes. Figure 2 represents sample frames of two video sequences with ground truth information of each frame marked manually as shown in column 1. Column 2 and column 3 present the implementation results of proposed method.

3 Performance Evaluation Metrics

The performance analysis of proposed algorithm has been based upon the performance evaluation metrics to quantitatively analyze the target detection performance in turbulent degraded image sequences. Generally, frame-based metrics [15] are used to measure the detection performance. These metrics are computed by the quantity of parameters such as true positive (TP), false positive (FP) and false negative (FN), defined as follows:

True Positive (TP): Numbers of frames where both ground truth and object detection results agree on the presence of one or more object, and the centroid of at least one or more detected object lies inside the bounding box of ground truth object.
False Positive (FP): Numbers of frames where object detection results contain at least one object, while ground truth either does not contain any object or none of the detected object's centroid falls within the bounding box of ground truth object.
False Negative (FN): Numbers of frames where ground truth contains at least one object, while object detection results either do not contain any object or none of the detected object's centroid falls within the bounding box of ground truth object.

In addition, we calculated statistical parameters—false alarm rate (FAR), precision (P), detection rate (DR), false negative rate (FNR), and F1 presented as follows:

$$\mathbf{FAR} = \frac{\mathbf{FP}}{\mathbf{TP}+\mathbf{FP}}, \mathbf{P} = \frac{\mathbf{TP}}{\mathbf{TP}+\mathbf{FP}}, \mathbf{DR} = \frac{\mathbf{TP}}{\mathbf{TP}+\mathbf{FN}}, \mathbf{FNR} = \frac{\mathbf{FN}}{\mathbf{TP}+\mathbf{FN}}, \mathbf{F1} = \frac{2 * \mathbf{P} * \mathbf{DR}}{\mathbf{P}+\mathbf{DR}} \tag{16}$$

4 Results and Comparison

The moving target detection algorithm proposed in this paper method was tested on recorded, atmospherically degraded video sequences and compared with the state-of-the-art method published in the literature [8] for moving target detection under similar imaging conditions. The video sequences used for evaluating the detection performance of the proposed method with published work are taken from resources available online at [10].

We have taken four video sequences, two with moderate strength of turbulence and other two with higher strength of turbulence. Sample frames from four video sequences are presented in Fig. 3. Each row in Fig. 3 shows frames from original recorded video sequences, while column 1 shows input frame with ground truth information. In Fig. 3, column 2 shows the detected targets using the proposed method and column 3 shows the results obtained using Eli Chen et al.'*s* method [8]. The ground truth moving targets were marked by green bounding boxes, and the

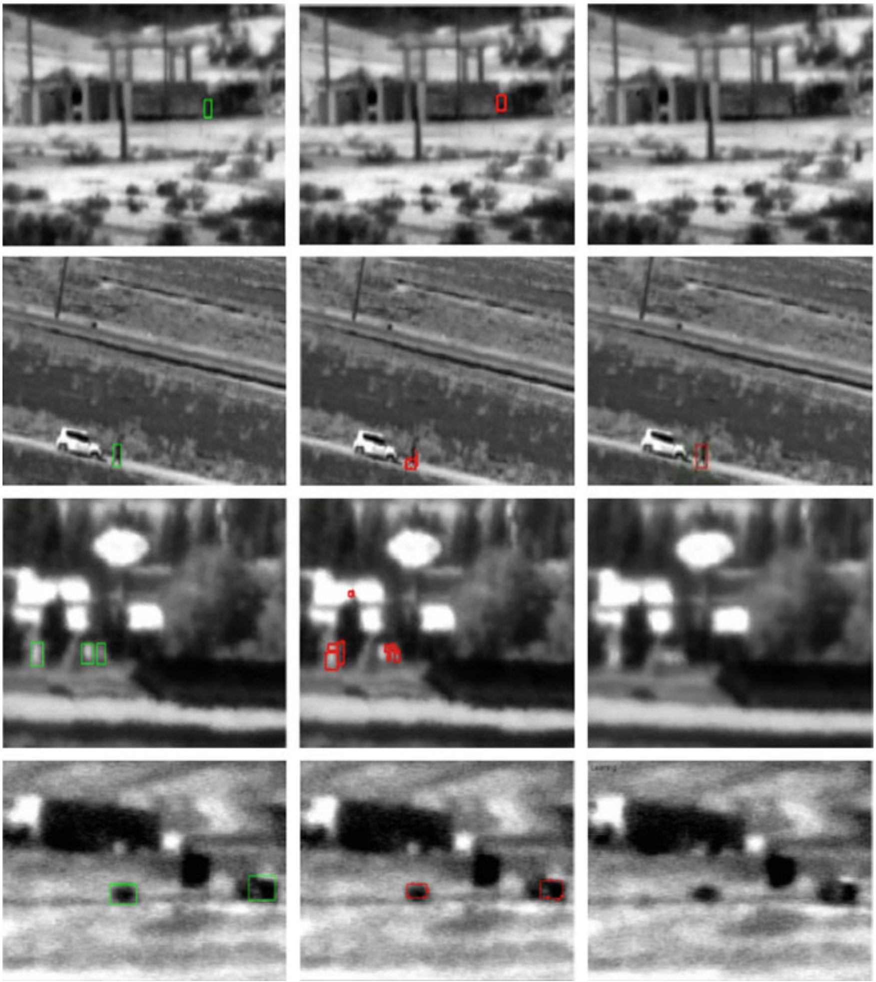

Fig. 3 Sample frames from video showing ground truth information and moving target detection results obtained using the proposed method and published method of [8]. The first column indicates ground truth of four video sequences; 1, 2, 3, and 4 with green bounding box. The second column shows the target detection using proposed method, and last column shows the results obtained using the method proposed by Chen et al. [8]. Detected moving objects are marked by red bounding boxes

detected moving objects using the proposed method and those obtained using Eli Chen et al. method are marked by red bounding boxes.

From the results shown in Fig. 3, it can be observed that the proposed algorithm performs better than the published method of [8] under both moderate and high turbulence conditions. It can be seen from the results given in Fig. 3 that the method used by Eli Chen et al. [8] results in some miss detection, which are detected using proposed algorithm.

We have carried out the performance analysis of the proposed algorithm with published method of [8] by computing numbers of true detection, false alarms, and miss detections over all the four videos taken from online resources of [10]. For quantitative comparisons, TP, FP, and FN are evaluated by two approaches: number of frame-based approach [15] and approach mentioned in Eli Chen et al. [8] work. The results are summarized in Tables 1 and 2.

We have also calculated the statistical parameters DR, P, FNR, and F1 from the results of Tables 1 and 2 for the proposed method and published method of [8]. Every parameter was averaged for two video sequences at both moderate turbulence strength and strong turbulence strength. The results are summarized in Table 3. It can be concluded from these parameters that the proposed algorithm produced better detection performance irrespective of the evaluation approach.

The performance metric F1 describes the harmonic mean of false alarm (FP) and miss detection (FN) with regard to TP (as shown in formula of F1 by Eq. 16), thus describing detection performance in the range of 0–1. A higher value of F1 means better detection performance of moving object detection algorithm. It can be seen from the graph given in Fig. 4 that the proposed method has higher F1, under both moderate and strong turbulence effects as compared to the state-of-the-art method used in [8], enabling better detection performance with proposed method.

Table 1 Dataset of the proposed method and published method of [8] on number of frame-based approach

Video sequence	Strength of turbulence	Proposed method			Published method of [8]		
		TP	FP	FN	TP	FP	FN
1	Moderate	185	226	45	49	0	72
2	Moderate	357	145	205	287	59	343
3	Strong	373	358	22	204	42	301
4	Strong	98	359	33	12	9	141

Table 2 Dataset of the proposed method and published method of [8] on approach mentioned in [8]

Video sequence	Strength of turbulence	Proposed method			Published method of [8]		
		TP	FP	FN	TP	FP	FN
1	Moderate	6	1	3	1	0	6
2	Moderate	15	0	6	7	0	13
3	Strong	20	2	0	9	0	11
4	Strong	0	0	6	2	1	0

Table 3 Performance metrics of the proposed method and published method of [8]. Each value was averaged for two video sequences

Strength of turbulence	Evaluation approach	Proposed method				Published method of [8]			
		P	DR	FNR	F1	P	DR	FNR	F1
Moderate	No. of frame-based approach	0.58	0.72	0.28	**0.63**	0.92	0.34	0.57	**0.47**
	Approach mentioned in [8]	0.93	0.69	0.31	**0.79**	1	0.25	0.76	**0.39**
Strong	No. of frame-based approach	0.36	0.85	0.16	**0.5**	0.72	0.27	0.76	**0.39**
	Approach mentioned in [8]	0.79	1	0	**0.88**	0.5	0.23	0.78	**0.31**

5 Conclusion and Future Work

This paper proposes simple and efficient method for detecting moving objects in long-range, turbulence degraded videos. We have tested this method on both visual and infrared video sequences degraded by turbulence. We have also compared the detection performance of our approach with the state-of-the-art method in varying degree of turbulence. Results obtained establish that the proposed algorithm performance is better under both moderate strength and higher strength of turbulence degraded video sequences. The method presented is generic in nature used for aerial-, marine-, and ground-based scenarios. We plan to further use this simple and effective target detection algorithm in video stabilization for removing atmospheric turbulence of long-range imaging systems.

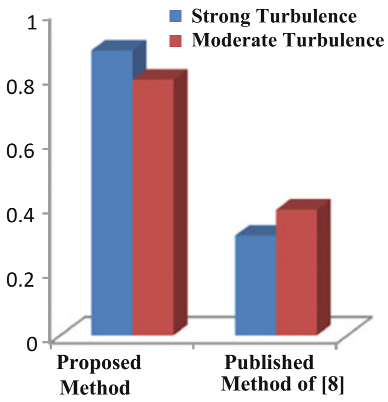

Fig. 4 F1 of the proposed method compared with state-of-the-art method of [8]. A higher value of F1 means better detection performance

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Effective Denoising with Non-local Means Filter for Reliable Unwrapping of Digital Holographic Interferometric Fringes

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Abstract Estimation of phase from the complex interference field has become an emerging area of research for last few decades. The phase values obtained by using `arctan` function are limited to the interval $(-\pi, \pi]$. Such phase map is known as wrapped phase. The unwrapping process, which produces continuous phase map from the wrapped phase, becomes tedious in presence of noise. In this paper, we propose a preprocessing technique that removes the noise from the interference field, thereby improving the performance of naive unwrapping algorithms. For de-noising of the complex field, real part and imaginary parts of the field are processed separately. Real-valued images (real and imaginary parts) are processed using non-local means filter with non-Euclidian distance measure. The de-noised real and imaginary parts are then combined to form a clean interference field. MATLAB's `unwrap` function is used as unwrapping algorithm to get the continuous phase from the cleaned interference field. Comparison with the Frost's filter validates the applicability of proposed approach for processing the noisy interference field.

Keywords Holographic interferometry · Non-local means · Non-Euclidian distance · Phase unwrapping · Image de-noising

1 Introduction

In interferometric techniques, physical quantities are encoded into phase, and hence reliable phase estimation becomes the major task. These techniques include synthetic aperture radar for surface topography, magnetic resonance imaging for mapping of

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B. B. Chaudhuri et al. (eds.), *Proceedings of 2nd International Conference on Computer Vision & Image Processing*, Advances in Intelligent Systems and Computing 703, https://doi.org/10.1007/978-981-10-7895-8_2

internal structure of the body, digital holographic interferometry and moiré for in-plane and out-off plane deformation assessment, fringe projection profilometry for 3D reconstruction of the object, digital holographic microscopy for study of microscopic biological objects, and many others. The term *phase* changes from method to method, e.g., in fringe projection profilometry, the phase means the phase of the sinusoids of the fringe pattern, whereas in holography, phase means the phase of the actual light wave. However, following equation represents most general form for the complex interference field [1].

$$\mathbf{\Gamma}(m, n) = a(m, n)exp\,(j\,\phi(m, n)) + \eta(m, n) \tag{1}$$

where $\Gamma(m, n)$ represents the interference field, $a(m, n)$ is the real amplitude, and $\phi(m, n)$ is the phase of the interference field. $\eta(m, n)$ is the noise and is assumed to be white Gaussian with zero mean and variance σ_η^2.

Several noise filtering techniques for the reduction of speckle noise in digital holographic interferometry for phase unwrapping have been developed in the past. For example, Sukumar et al. [2] proposed Kalman filter for denoising in post-processing step to restore the unwrapped phase without any noise. Several other techniques such as Fourier transform profilometry [3], windowed Fourier transform profilometry [4], wavelet transform profilometry by [5] have been proposed over last three decades for the analysis of these fringe patterns. The phase map generated by most of these methods is noisy and wrapped. This requires careful selection of the combination of proper noise filtering [6–8] and phase unwrapping algorithms [9–12].

The noise filtering algorithms developed so far assumes the noise to be additive Gaussian. In digital holographic interferometry (DHI) and synthetic aperture radar (SAR), the interference fields are generated using coherent sources that produce speckle pattern on the surface of the object under test. Speckle noise is a type of noise where an undesirable signal gets multiplied with the original image, as opposed to additive Gaussian noise where noise gets added to the intended signal giving rise to a degraded image. Due to this reason, speckle noise is known to be multiplicative noise. If the original image is represented by $g(m, n)$ and speckle noise by $\eta(m, n)$, then the degraded observation $h(m, n)$ is given by:

$$h(m, n) = g(m, n)\,.\,\eta(m, n) \tag{2}$$

where (m, n) indicate the pixel location.

Speckle noise suppression has been a challenging task for long time. De-noising methods began with techniques relying on local statistics. Lee et al. [6] and Kuan et al. [13] proposed adaptive speckle suppression filters by making use of the local