ALGORITHM FOR COMPENSATION OF ATMOSPHERIC TURBULENCE FOR LONG-RANGE VIDEO SEQUENCES COMPRISING ACTUAL MOVING TARGETS

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Abstract: Presence of optical turbulence in the atmosphere over horizontal imaging pathways, limits the recognition range, target detection, and identification performance of imaging systems, especially those intended for video surveillance. This paper proposes a stabilization algorithm that compensates for geometric distortions in turbulence degraded videos while preserving the motion of real moving objects in the target scene. The proposed algorithm uses a block matching method with an infinite impulse response filter to provide stabilization. The detailed performance analysis from turbulence degraded video sequences is evaluated through performance metrics. Quantitative results show that this proposed algorithm can effectively decrease the turbulence intensity and can substantially mitigate geometric distortions.

Key words: long-range imaging through turbulent media, atmospheric turbulence compensation, block matching, video stabilization, performance parameters.

1. INTRODUCTION

The recognition range and visual quality in surveillance systems, especially for ground-to-ground observation along a horizontal path, are severely degraded as a result of optical turbulence in the atmosphere. Turbulence is a random, non-linear optical phenomenon that occurs in the atmosphere. Generally, the temperature gradients, present in the atmosphere, are the main cause of turbulence and these variations in temperature turn out to be refractive index fluctuations. These variations allow the image to focus at various points in the receiving optics' focal plane, creating turbulence distortions [1].

Turbulent media as imaging path results in blurry and wavering of the target scene, which imposes limitations on vision systems used to record long-range target scenes, resulting in a loss of information in the target scene. As a consequence, image quality is generally degraded by the presence of turbulence rather than the quality and accuracy of the imaging system used [2]. In order to recover the real details of the target scene, it is therefore important to compensate for the visual degradation caused by the effects of turbulence.

For the compensation of atmospheric turbulence effects, a number of approaches have been suggested. Most are related to hardware-based techniques that have proved effective in the treatment of vertical imaging as in the field of astronomy. However, in imaging over the horizontal path, the conditions are anisoplanatic. In such conditions, light from each point in the target scene acquires a slightly different low order aberration under, causing the image of these points to be spontaneously displaced from their proper geometric position [3]. Turbulence compensation by hardware techniques cannot accomplish the goal of improving the entire image that is degraded by anisoplanatic conditions [3]. In such cases, techniques focused on image processing have been suggested [3-5], so turbulence for existing video sequences can be compensated.

Numerous image processing algorithms [3-15] have been proposed for the compensation of atmospheric turbulence effects; Patel et al. proposed an improved version of the Sobolev Gradient and Laplacian (SGL) algorithm to mitigate turbulence effects in distorted images [3]. Maor et al. used global video stabilization and then proposed a method for tracking moving objects in turbulent distorted videos [4]. Gepshtein et al. [5] proposed a differential image elastic registration method to find the translation vector for each pixel in each frame to inverse wrap the image to its true geometry. It stabilizes steady parts of the scene while preserving the real motion in sequences. However, it is computationally intensive. Huebner et al. [2], [6] proposed a motion-compensated image integration procedure with blind deconvolution algorithms for restoration of atmospherically degraded imagery. This method does not preserve the real motion of objects; therefore motion-related problems are present in this method. The methods based on Control Grid Interpolation (CGI) and Adaptive Control Grid Interpolation (ACGI)as discussed in references [7-9] lack a mitigating sequence that has a high amount of scintillation. Eekeren et al. [10] proposed a flexible, robust, and fast method for turbulence compensation in static scenes. It performs the registration using local processing. However, it is not suitable for imagery containing moving objects. Oreifej et al. [11] suggested a method for restoring the stable background without harming the actual motion of moving objects. This method, on the other hand, is computationally intensive and necessitates a significant amount of memory and computation. Halder et al. [12] proposed a stabilization method in which stable background is obtained by estimating the average shift of the pixel intensities over the distorted frames. Moving object regions are identified by this background and replaced by their raw pixel values. In this way a stabilized video sequence is generated. However, it is computationally intensive. Nieuwenhuizen [13] presents turbulence compensation in the presence of large moving objects using optical flow estimation technique. In reference [14], a registration-based approach is used to mitigate erratic motions due to turbulence and preserves the moving objects in video. Jing Wu [15] used optical flow-based registration, which results in a longer processing time. Following are the limitations of the above-discussed methods-

I. Turbulence compensation (TC) is a challenging task when there are actually moving targets in the imaging scene since turbulence-induced displacements would be superimposed on the displacement of the real moving objects.
II. Many TC methods use a global approach, which means they apply the same procedure to the whole picture, whereas conditions are likely to be isoplanatic when imaging along a long horizontal path, the effects of atmospheric turbulence is local rather than global only.

Such limitations can be solved by searching for an algorithm that can handle local as well as the global nature of turbulence in order to minimize the effect of atmospheric turbulence on long-range ground-to-ground imaging systems. This work proposes an algorithm for the compensation of atmospheric turbulence at the global and local levels while keeping the actual moving targets unharmed. To preserve the actual motion in the scene, firstly moving target detection algorithm is used and then the TC algorithm is applied only to the dynamic background of video frames. The proposed algorithm uses block matching for estimating and compensating image displacements between video frames. The motion-compensated frames are then processed with an Infinite Impulse Response (IIR) filter to provide stabilization. We have tested both global and local processing approaches on various real turbulence degraded videos. Both methods were implemented in the Matlab (R2016a) environment and detailed performance analysis from several sets of real atmospheric turbulence degraded video sequences is evaluated through performance metrics. Quantitative results illustrate that this proposed method can effectively reduce the strength of turbulence in real atmospheric turbulence degraded video sequences and capable of alleviating geometric distortions considerably.

The article is organized in the following way: Section 2 shows the proposed TC algorithm's block diagram as well as video stabilization strategies. Section 3 discusses the simulation results of the proposed algorithm. Finally, in Section 4, we come to a conclusion and explore possible study paths.

2. PROPOSED ALGORITHM

Figure 1 depicts a schematic block diagram of the proposed TC algorithm. This block diagram consists of two main segments; in the first segment, the moving objects are detected using the moving target detection algorithm specified in our previous work [16]. Next, the proposed turbulence compensation algorithm is applied only to the dynamic background. Finally, real moving targets are combined on the stable background so the output is stabilized video with real moving targets.

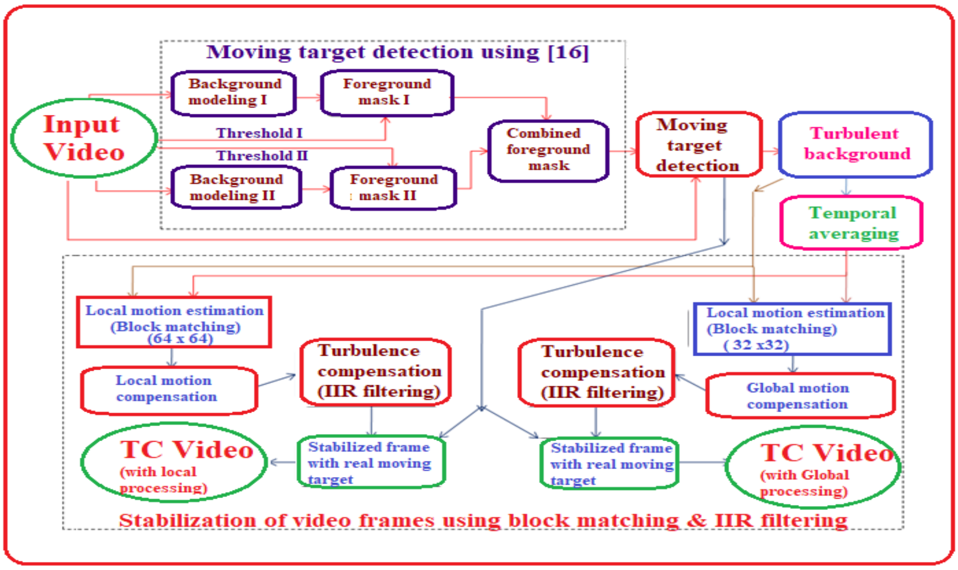

Fig.1. Block diagram of proposed TC algorithm

In this study, the following techniques are used for the TC algorithm-

2.1. Temporal averaging-

To stabilize turbulence degraded video, a reference frame is required and the reliability of the reference frame yields satisfactory results [17]. This is because the reference frame serves as the foundation for determining motion between images. In the case of effective turbulence strength, when observing moving targets, a temporal average-based reference image gives the best results [17]. In the present work, the temporal average-based reference frame is used to estimate the local image displacements. Let $I_n(x, y)$be the current frame, and *(x, y)*be the pixel coordinates of the image then reference frame is defined as:

$$\mathrm{R}(x, y) = mean(I_t(x, y)) \tag{1}$$

where $t = n + 1, n + 2, \ldots \ldots . . n + N$ and $R(x, y)$is the reference frame generated using temporal average filtering with window size *N = 15*.

2.2. Block matching

Block matching is the most widely used technique to estimate motion between video frames. The motion between the current frame and the reference frame is observed block by block by moving of block in the current frame to match the corresponding block in the reference frame within a specified pixel search space.

The basic idea of shifting the individual blocks of an image to match the block of the reference image gives a motion vector for each block. These local motion vectors represent local image displacements or image dancing. The basic idea of block matching is shown in figure 2.

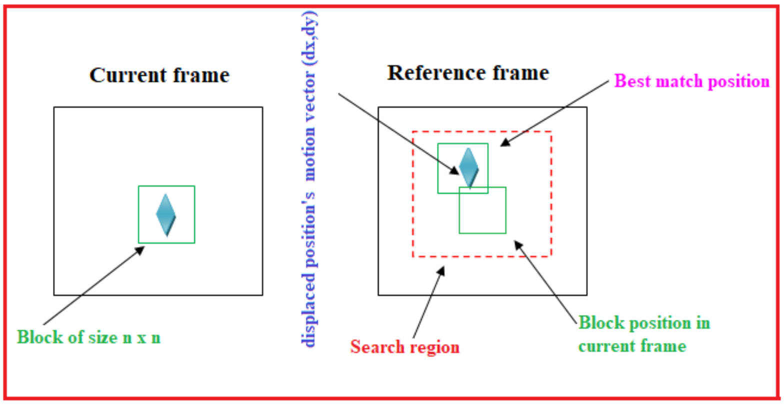

Fig.2. Block matching to estimate motion vectors

The input frame is divided into blocks of size (*n x n*) pixels. This block is searched in a reference frame within the given search region for matching. The method used for matching determines the accuracy of the motion estimation. The most popular matching methods are Normalized Cross-Correlation (NCC), Mean Absolute Difference (MAD), and Mean Squared Difference (MSD). Due to its lower statistical complexity, the MAD is the most commonly used matching criterion [2].In the present work, block matching with MAD is used for calculating motion between the current and reference frames. Each frame is divided into blocks of size (32 x32) pixels to estimate local image displacement. Further, for local turbulence compensation, another block-matching approach is used in which each frame is divided into a block size of (64 x 64) pixels. In both of the block matching approaches, the smallest MAD overall potential displacements (*dx, dy*) within the search region are used to calculate the motion vector.

2.3. Image registration

The estimated motion is compensated using image registration operation i.e. input frames are translated on the basis of motion vectors. A single motion vector is computed on the basis of statistics on local motion vectors for each individual frame. In the present work, the Median (MED) based and Vector Angle Histogram (VAH) based method is used to find global motion vector. Each of these statistical methods is given in [18].

2.4. Infinite Impulse Response (IIR) filtering

Stable frames are generated using an IIR filter in the present work of TC. This is an advanced version of the normal averaging filter; the main distinction is that prior to averaging, the current frame is shifted slightly to best match the reference frame. These motion-shifted frames are averaged to reduce the image dancing between one frame and the next. Also, the stabilization effect for the IIR filter is generally better than the simple averaging filter [2]. In the proposed stabilization algorithm, we defined the ratio updated averaging as:

Let $I_n(x, y)$be the input frame, *(x, y)* be the coordinates of the image. We defined the reference frame using equation (1) and $S_n(x \pm dx,\ \mathrm{y}\ \pm \mathrm{d}y)$ is the shift for the current frame. Then the motion-compensated frame is defined as:

$$\tilde{\mathrm{I}}_n(x, y) = (I_n(x, y) \pm S_n(x \pm dx,\ \mathrm{y}\ \pm \mathrm{d}y)) \tag{2}$$

Let O_{n+1} is the current output and O_n is the previous output then the motion-compensated averaging is defined as:

$$O_{n+1} \ = \beta\left[\alpha O_n + (1-\alpha)\tilde{\mathrm{I}}_{n+1}\right] + \ (1-\beta)I_n \tag{3}$$

where the values of α, β are taken to be 0.6 for the proposed work. The stable frames with turbulence compensated background and unaffected real moving targets are the output of the stabilization process.

2.5. Turbulence Compensation

In the proposed TC algorithm, the geometric distortion has been corrected at a global scale and local scale. Each of the global and local processing has been discussed as:

Global TC. To correct the geometric distortion at the global level, the IIR filter is used on frames that are compensated for motion at the global level. As discussed in the block matching and motion compensated section, the estimated motion is computed using MED and VAH-based statistics on local motion vectors. Therefore each frame has the same amount of motion shift for all pixels i.e. the whole image. Further, these compensated frames are stabilized using an IIR filter.

Local TC. To correct the geometric distortion at the local level, the IIR filter is used on the local motion-compensated frames. As discussed in the block matching and motion compensated section, the estimated motion is computed using block-matching and each frame has *N* number of local motion vectors i.e. one motion vector for each block. This local motion is compensated using geometric transformation on each block of a current frame and stabilization is done using an IIR filter. The seamless frames are generated using image stitching with GIST [19].

3. SIMULATION RESULTS

The proposed algorithm is simulated in MATLAB (R2016a) installed in a 64-bit Windows operating system with 4GB RAM on a real-world dataset.

3.1. Dataset

To test the performance of the proposed algorithms, several sets of image sequences were recorded under atmospheric turbulence. For the purpose of the result, only two video sequences have been given. Table 1 summarizes the different parameters for recorded video sequence1 and video sequence 2.

Table 1.Dataset parameters

Parameter	**Video sequence 1**	**Video sequence 2**
Resolution	576 x 704	576 x 704
Number of frames	9259	2105
Optics diameter (mm)	100	100
Wavelength (μm)	0.55	0.55
Target distance (Km)	10	12
PFOV (μrd)	6	6
Frame rate (Hz)	25	25

3.2. Qualitative results

The results presented in figure 3 show that the proposed stabilization approaches of Global TC and Local TC alleviate geometric distortions considerably. In figure 3, the first row represents sample frames from video sequence 1 and video sequence 2. Each of the video sequences containing real moving targets and the ground truth information of real moving targets is represented by a red color bounding box. The second row of figure 3 shows the moving target detection results by using our previous algorithm mentioned in reference [16] and the detected target is surrounded by a red color bounding box. The third row shows the turbulent background scene (not containing any moving target) that is to be stabilized in order to mitigate the geometric distortions caused by atmospheric turbulence. In figure 3, the fourth, fifth, and sixth row represents the results of proposed stabilization methods of Global TC (using VAH), Global TC (using Median), and Local TC, respectively. The output frames are stable frames having the motion of real moving targets only.

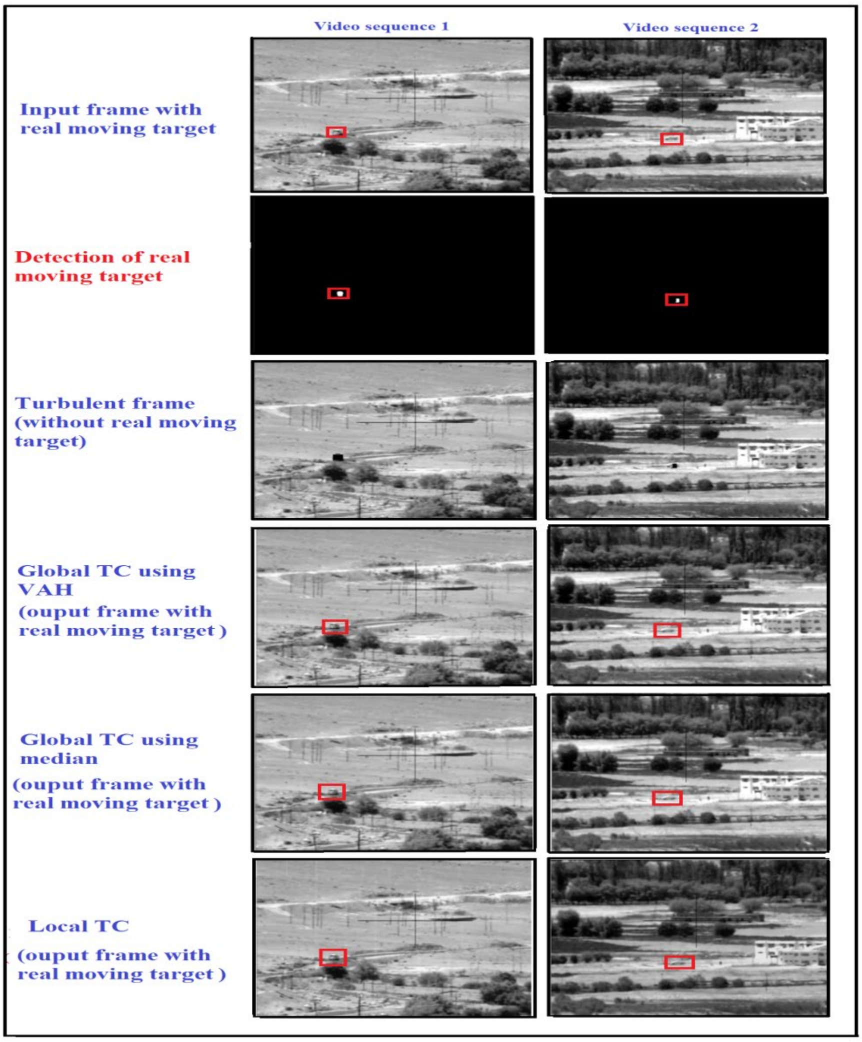

Fig.3. Sample frames from video sequence 1 and video sequence 2 showing results of stabilization algorithm

3.3. Quantitative results

For a quantitative assessment of the performance of the proposed stabilization method, several performance metrics are computed for unprocessed (turbulent) video and processed (turbulence compensated) video. The performance metrics used for measurement can be Mean Squared Error (MSE), turbulence strength estimation in terms of refractive index structure parameter (C_n^2), Structural Similarity Index

Measure (SSIM), and the variance of an invariant pixel position. Also, the performance of proposed algorithms is compared against the standard algorithm of feature-based image registration that is commonly used for geometric correction in images and directly available in Matlab [22]. We run the feature-based image registration algorithm and proposed algorithm on the recorded data set as given in subsection 3.1 and computed the performance parameters. The observed value of performance parameters are as:

3.3.1. MSE

Mean Squared Error is the measure of the average of the squared compensation error. It is used to evaluate the turbulence compensation quality and can be measured between consecutive frames (when the original video is not available). This performance parameter shows the stability of the sequence. The geometric differences between consecutive frames would be significant if turbulence is present, resulting in a high MSE, while the MSE variations for the turbulence corrected sequences are reduced. Figure 4 represents the plot of MSE for unprocessed and processed videos. The blue line curve shows the value of MSE for unprocessed video sequences. In the case of turbulence compensated video sequence1 and video sequence 2, MSE is low, indicating stability in video sequences.

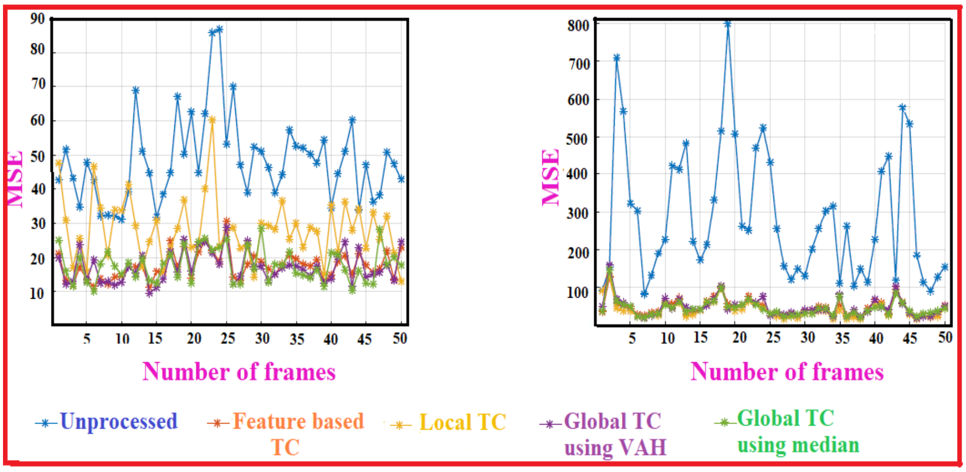

Fig.4. MSE between successive frames of video sequence 1 and sequence 2

3.3.2. Turbulence Strength Estimation (C_n^2)

C_n^2 is the refractive index structure parameter that expresses the strength of turbulence. This parameter was estimated using the Zamek-Yitzhaky turbulence estimation algorithm given in [20] for unprocessed and processed video sequences. In comparison to the unprocessed video sequence, the estimated value of C_n^2 is reduced for the turbulence compensated video sequence.Figure5 shows the estimated value of the refractive index structure parameter for unprocessed and processed video sequences. The blue line curve indicates the estimated value of turbulence strength present in the unprocessed video. All other curves represent the turbulence strength for turbulence compensated video sequences. Here, more reduction in turbulence strength is obtained using the proposed TC algorithm as compared to the standard feature-based algorithm.

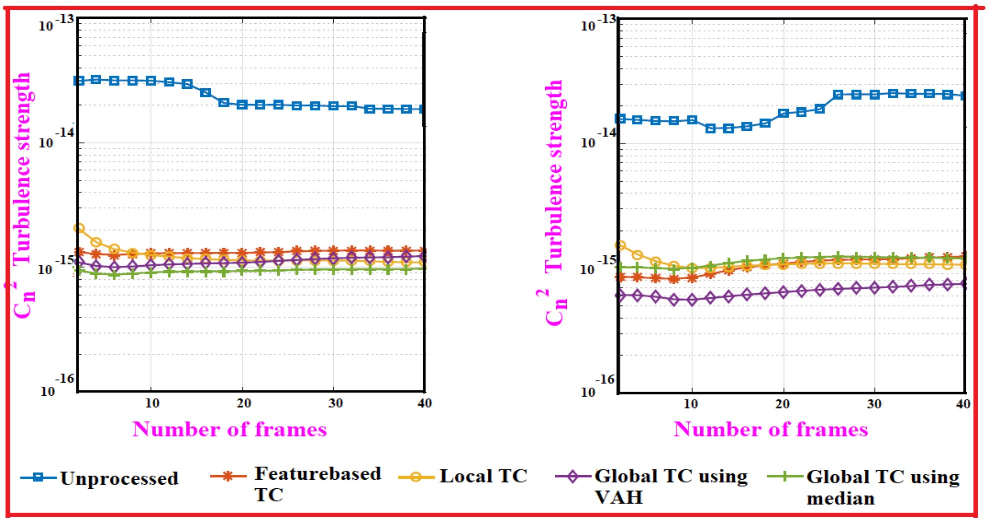

Fig.5. Plot of c_n^2 with a number of frames for video sequence1 and sequence 2 showing reduction in strength of turbulence.

3.3.3. SSIM

Wang et al. proposed SSIM to provide a quantitative estimation of similarity between two images [21]. Mathematically, the similarity measure between two images with the same dimension is given as [22]

$$SSIM(p,q) = \frac{(2\mu p\mu q + w1)(2\sigma pq + w2)}{(\mu p^2 + \mu q^2 + w1)(\sigma p^2 + \sigma q^2 + w2)} \qquad (4)$$

where, $\boldsymbol{\mu q}$, $\boldsymbol{\sigma p}$,$\boldsymbol{\sigma q}$, and $\boldsymbol{\sigma pq}$ are the local means, standard deviations, and cross co-variance for image $\boldsymbol{p}$ and image $\boldsymbol{q}$. This metric is one of the most often used when comparing turbulence compensation algorithms. [23]. When the original video sequence is not available then SSIM can be measured between consecutive frames and the value of this index represents the influence of turbulence in a video sequence. SSIM gives a similarity index between 0 and 1. A higher value of SSIM indicates better stability in the image sequence.The SSIM between consecutive frames of unprocessed and processed video sequences is shown in figure 6. The blueline curve represents the SSIM values of unprocessed video sequences. All the processed video sequences have greater similarity in consecutive frames showing stability in processed video sequences.

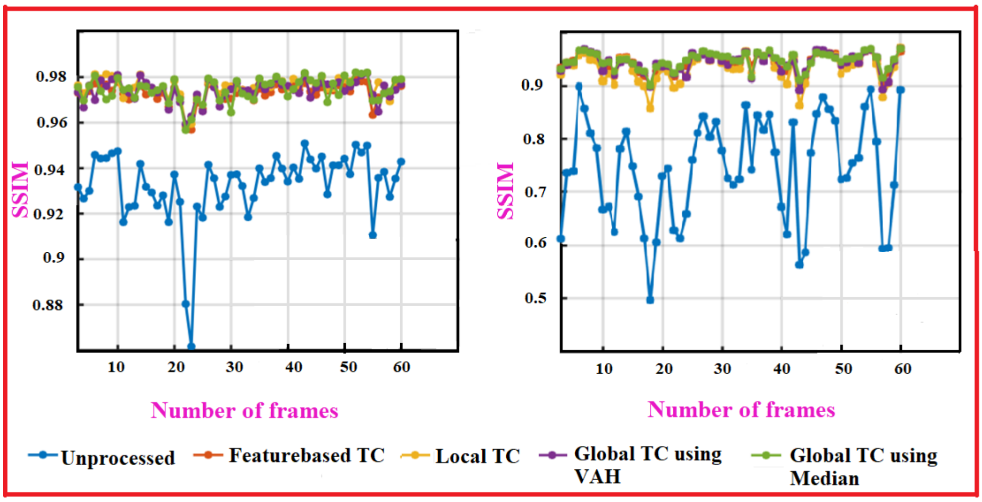

Fig.6. Similarity index of video sequenc1 and video sequence 2

3.3.4. Positional variance of an invariant point

This plot is used to correlate the position variance of an invariant point on the first frame of turbulence degraded video sequence with the rest of the frames i.e. how the position of this point varies for the recorded video sequence that is degraded by turbulence. Now the same point's position change can be calculated for turbulence corrected sequence. By this positional variance parameter, one can compare the performance of their stabilization algorithm. The least variance shows better stability in processed video sequences. In figure 7, the blue line indicates the variance in the position of an invariant point in frames of unprocessed video sequences. This position of point has the least variance for processed video sequences.

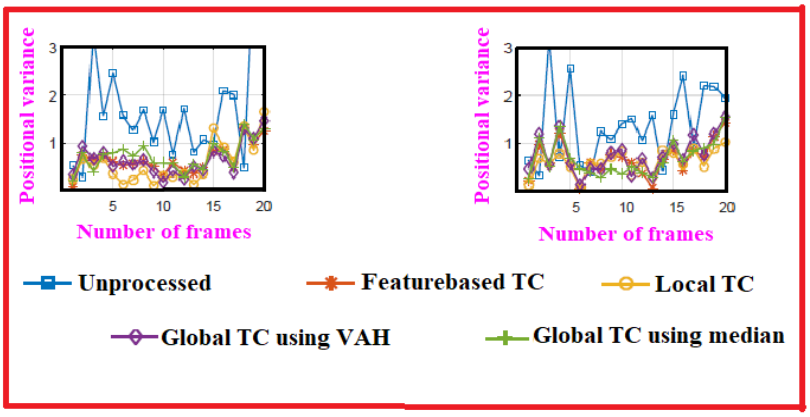

Fig.7. Positional variance of an invariant point for video sequence 1 and sequence 2

It can be observed from the testing parameters that the performance-wise local turbulence TC method has more reduction in MSE, C_n^2 turbulence strength, positional variance, and higher index of similarity. However, complexity is higher in the local TC method as compared to the global TC methods.

4. CONCLUSION

A turbulence compensation algorithm is presented to mitigate the effects of atmospheric turbulence on long-range surveillance imaging. A stable background scene has been estimated using block-matching and IIR filtering at global and local processing. The testing parameters of stabilized video sequences show that the proposed TC algorithm of video stabilization can recover the real detail of the target scene even if it contains actual moving objects. Future work includes the implementation of the presented algorithm on Field-Programmable Gate Array (FPGA)-based hardware for real-time processing to alleviate the effects of atmospheric turbulence on long-range imaging.

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