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Mollifying Atmospheric Instability in Video Surveillance System Using DT-CWT

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ABSTRACT: Atmospheric instability is a challenging problem in video surveillance. This paper describes a new method for mollifying the effects of atmospheric distortion on observed images, particularly in distorted video turbulence which degrades a region of interest (ROI) .Due to this valuable information from video can be lost, and distorted video is of no use. So to extract important information or data from distorted video use CLEAR algorithm which retrieve information from distorted video. This paper describes a new method for mollifying the effects of atmospheric instability on observed images, particularly airborne turbulence which degrades a region of interest (ROI).In order to provide accurate detail or data from objects behind the distorting layer, a simple and efficient frame selection method is proposed to get informative ROIs from only good-quality frames. We solve the space-variant instability called distortion problem using region-based fusion based on the Dual Tree Complex Wavelet Transform (DT-CWT). We also propose an object alignment method for pre-processing the ROI since this can exhibit significant offsets and distortions between frames. Simple haze removal is used as the final step. To remove the haze from distorted video we use the CLEAR algorithm to extract important information from video. The CLEAR algorithm has series of step to clear video and lastly get restored image. For last step i.e., haze removal dark channel prior method is used. The proposed method performs very well with atmospherically instable or distorted video and outperforms other existing methods.

KEYWORDS: Dual tree complex wavelet transform, (DT-CWT), image restoration, fusion.

I. INTRODUCTION

The use of surveillance videos in the open environments such as traffic signals are very important.The video signals may be affected due to some distortions such as fog haze etc.The informations in the videos are extracted by using CLEAR.It consists of a series of steps to recover the informations from the video frames.The ROI is selected and then the distorted images are aligned.Then from the good quality frames the ROI were extracted and then fused to get a clear Image.

VARIOUS types of atmospheric distortion can influence the visual quality of video signals during acquisition.Typical distortions include fog or haze which reduce contrast,and atmospheric turbulence due to temperature variations or aerosols. In situations when the ground is hotter than the air above it, the air is heated and begins to form horizontal layers.When the temperature difference between the ground and the air increases, the thickness of each layer decreases and the air layers move upwards rapidly, leading to faster and greater micro-scale changes in the air's refractive index. This effect is observed as a change in the interference pattern of thelight**.**

Since turbulence in the captured images makes it difficult to interpret information behind the distorting layer, there has been significant research activity trying to faithfully reconstruct this useful information using various methods. The perfect solution however seems impossible since this problem is irreversible.
although it can be simply written as Eq. 1.

$$\mathbf{I}_{obv} = \mathbf{DI}_{idl} + \varepsilon. \qquad (1)$$

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where Iobv and Iidl are the observed and ideal images respectively.D represents geometric distortion and blur, while "represents noise. Various approaches have attempted to solve this problem by using blind deconvolution (BD) [1, 2]. The results, however, still exhibit artefacts since the point spread function (PSF) is assumed to be space-invariant. It is obvious that using a single image is not sufficient to remove the visible ripples and waves, while utilising a set of images to construct one enhanced image makes more useful information available. There are two types of restoration process that use multiple images.

The first employs image registration with deformation estimation to align objects temporally and to solve for small movements due to atmospheric refraction [3, 4]. Then a deblurring process is applied to the combined image (which is a challenging task as this blur is space-variant). The other group employs image selection and fusion, known as 'lucky region' techniques [5]. The regions of the input frames having the best quality in the temporal direction are selected and then are combined in an intelligent way. Recently this method has been improved by applying image alignment to those lucky regions [6]. In this paper, we propose a new fusion method to reduce image distortion caused by air turbulence. We employ a region-based scheme to perform fusion at the feature level. This has advantages over pixel-based processing as more intelligent semantic fusion rules can be considered based on actual features in the image.

The fusion is performed in the Dual Tree Complex Wavelet Transform (DT-CWT) domain as it provides near shift-invariance and directional selectivity [7]. Additionally, the phase of a CWT coefficient is robust to noise and a temporal intensity variation thereby providing an efficient tool for removing the distorting ripples. Before applying fusion, a set of selected images or ROIs must be aligned. We introduce an object alignment approach for distorted images. As randomly distorted images do not provide identical features, we cannot use conventional methods to find matching features. We, instead, employ a morphological image processing technique. Subsequently we select the ROI (or whole image) from only the informative frames measured by a novel quality matric, based on sharpness, intensity similarity and ROI size. Then a non-rigid image registration is applied. After the fusion, haze and fog are removed using a locally adaptive histogram equalisation.

II. RELATED WORK

a. *Registration using DT-CWT:*

The Dual Tree Complex Wavelet Transform (DT-CWT) introduced by Kingsbury is a form of discrete wavelet transform which generates complex coefficients using a dual tree of wavelet filters to obtain their real and imaginary parts. Although this redundancy factor of two costs extra computational power, it provides extra information for analysis and also still allows perfect reconstruction of the signal. The DT-CWT overcomes some of the problems of traditional discrete wavelet transforms in image processing as it provides properties of near shift-invariance and directionally selectivity [4].

Registration of non-rigid bodies using the phase-shift properties of the DT-CWT was proposed in [4]. The algorithm is developed from the ideas of phase-based multidimensional volume registration, which is robust to noise and temporal intensity variations. Motion estimation is performed iteratively, firstly by using coarser level complex coefficients to determine large motion components and then by employing finer level coefficients to refine the motion field. The motion is described locally as a parametric affine model.

b. *Image Fusion*:

Fusion of images and video sources is becoming increasingly important for various applications, particularly for surveillance, where visible and infrared (ir) images need to be fused. Pixel-level fusion methods are computationally efficient and easy to implement since the originally measured values are directly involved in the fusion process. The performance of various pixel-based image fusion methods both in the spatial domain (average and principal component analysis (pca)), and in the transform domain (contrast pyramid, gradient pyramid, discrete wavelet transform (dwt), shift invariant dwt (sidwt) and dual-tree complex wavelet transform (dt-cwt)) is studied. In addition, the key parameters of the wavelet transform are examined to establish how suitable they are for image fusion, particularly in the context of visible and infrared image sequences, in terms of the quality of the fused result and computational complexity. Using both qualitative and quantitative analysis of the fused images and some theoretical considerations, a number of key

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recommendations are made suggesting what fusion method and parameters constitute the best choice in various applications.

Fusion Methods:

Various image fusion methods were studied listed as follows.

- Average intensity: Fused image is generated by averaging all input images.
- Principal Component Analysis (PCA): Input images are combined using weighted average computed from the PCA. The weights are computed from the PCA coefficients with the highest eigen values [2].
- Contrast Pyramid: A multi-resolution image pyramid is constructed from registered input images using Laplacian transform. Judgments of the important parts of the image are based on the local luminance contrast. A maximum absolute contrast scheme is used to choose between importance of pixels of the image at various levels in the decomposed image. This method can have problems with noisy images as the noisier image typically has high contrast and thus will be selected over a cleaner image.
- Gradient Pyramid: Image pyramid is constructed using adapted Laplacian transform. The gradient operators used in the horizontal, vertical, and 2 diagonal directions. Then, the maximum selection rule is applied for fusing each decomposed image.
- Discrete Wavelet Transform (DWT): Wavelet transforms have been successfully used in many fusion schemes. The discrete wavelet transform (DWT) is a spatial-frequency decomposion that provides a flexible multi-resolution analysis of an image [4]. The DWT involves filtering and down sampling the signal. Provided that the analysis filters used are biorthogonal, they will have a related set of synthesis filters which can be used to perfectly reconstruct the signal. The DWT has a number of advantages over pyramid-based schemes. For example, the wavelet transform provides directional information about the image, while pyramids do not contain any spatial orientation selectivity in the decomposition process. Pyramid-based fused images often contain blocking artifacts when regions in different images are significantly different. Fewer artifacts occur in wavelet fused images. The wavelet transform also gives better signal-to-noise ratios, and improved perceptual quality when human analysis is involved.
- Shift-Invariant Discrete Wavelet Transform (SIDWT) The main drawback of the DWT is that it is not shift invariant. This means that small shifts in the input signal can cause large changes in the energy across the sub-bands at the different levels. Shift invariance within wavelet transform image fusion is essential for the effective comparison of the coefficient magnitudes by the fusion rule. This is because the magnitude of a coefficient within a shift variant transform will often not reflect the true transform content at that point. This is due to the sub-sampling used in the DWT, necessary for critical decimation. The Shift Invariant Discrete Wavelet Transform (SIDWT) [7] is therefore introduced for image fusion. A SIDWT yields an over-complete signal representation as there is no sub-sampling, thereby leading to high complexity.
- Dual-tree complex wavelet transform (DT-CWT) with maximum selection, shown as DT-CWT MAX'. The DT-CWT provides near shift-invariance and better directional selectivity, with less memory and computational cost compared to the SIDWT [10]. It employs two fully decimated trees, one for the odd samples and one for the even samples generated at the first level. This increases directional sensitivity over the DWT and allows one to distinguish between positive and negative orientations. These properties of the DT-CWT lead to improvement in fusion results over the traditional DWT.
- Dual-tree complex wavelet transfor m (DT-CWT) with model-based weighted average using generalised Gaussian distribution (GGD).

c. Blind Deconvolution:

Classical deconvolution does not give impressive image restoration results when applied to short exposure images of which the distortions are spatially-phase-invariant. The method relies on the estimation of the PSF usually obtained from a theoretical model or an auxiliary measurement. When such data are not available, it becomes a blind deconvolution. Blind deconvolution is generally exploited to achieve (either or both of) image restoration and image enhancement. The goal of restoration is to accomplish an accurate depiction of the scene being imaged, while the enhancement aims to create the most visually appealing image (e.g. by removing noise).

Blind deconvolution estimates the PSF from the image (or images) itself and generally operates iteratively. In each iteration the image is improved at the same time of PSF estimation. Referring to Equation 1, only I_{obv} is

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known, so I_{idl} can result from the prediction using a generic measurement of the distance between these two data. A simple but effective method for solving this inverse problem is a least square method. Let x and y are vectors containing the I_{idl} and I_{obv}, respectively. H is a square, block-circulant matrix of the blurring function. Using L_2 norm, the x is estimated by minimizing $\|Hx - y\|^2$ with a non-negativity constraint. The regularization terms R and λ control the smoothness.

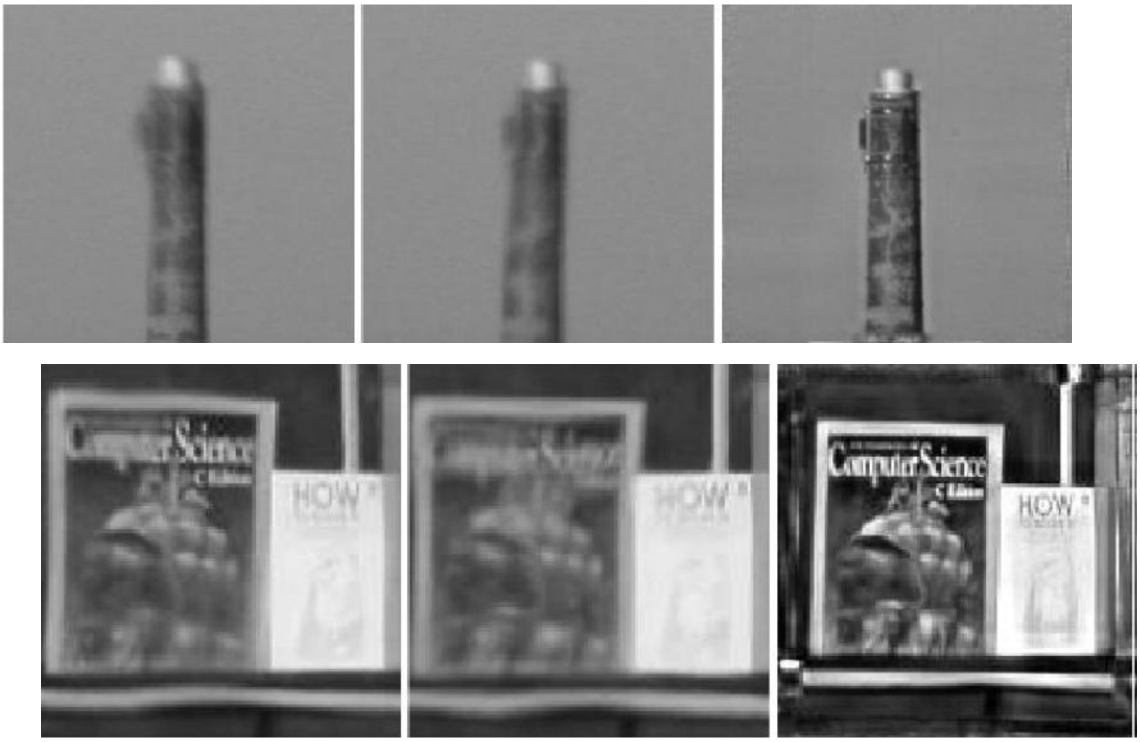

Figure 1: Chimney and books sequences. (a)-(b) observed frames. (c) reconstructed frame **.**

$$\hat{x} = \text{ARG}\, min_{x\geq 0}\|Hx - y\|^2 + \lambda R \qquad (1.1)$$

Generally in the first iteration, x is initialised by the first observation $y^{(0)}$. Even though the blind deconvolution can theoretically solve unknown prior information problems, the initial blur function H is important as it has to ensure that the iteration does not converge to the wrong solution. Additionally, the computation time of the process can be reduced with an accurate initial blur function H leading to a fewer iterations. That is, the key of this method is the application of a priori knowledge about the nature of the degradations and the images. The simplest solution is a Gaussian function which seems to work well with long-exposure images [2], but for short-exposure images the function should be considered locally.

When multiple frames are used, the blur function can be estimated with a least squares method using all available observed images $N, y^n, 0 < n \leq N$ [4].

$$H^{(t)} = \arg min_{H\geq 0}\left\|Hx^{(t)} - y^2\right\|^2 \qquad (1.2)$$

Blind deconvolution has been mainly applied to images where the blur function is space invariant. However, if artifacts (e.g. edge ringing) occur, they are not isolated events within the image. Hirsch et al. have introduced a space-variant blind deconvolution [7]. This method divides each frame into overlapping patches. Because the size of these patches is small, they can be viewed as isoplanatic regions - small regions containing space-invariant blur. Then, it can be processed through its individual FFT filter. That means the blind deconvolution algorithm estimates the PSF for each patch along with the latent image content. The final output image is produced by fusing the deconvolved patches. Example results are shown in Figure 1.

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Maximum likelihood estimation is also employed to solve the blind deconvolution problem; however, the computation complexity is generally high. Figure 2 shows image improvement with the sharpness after applying the blind deconvolution.

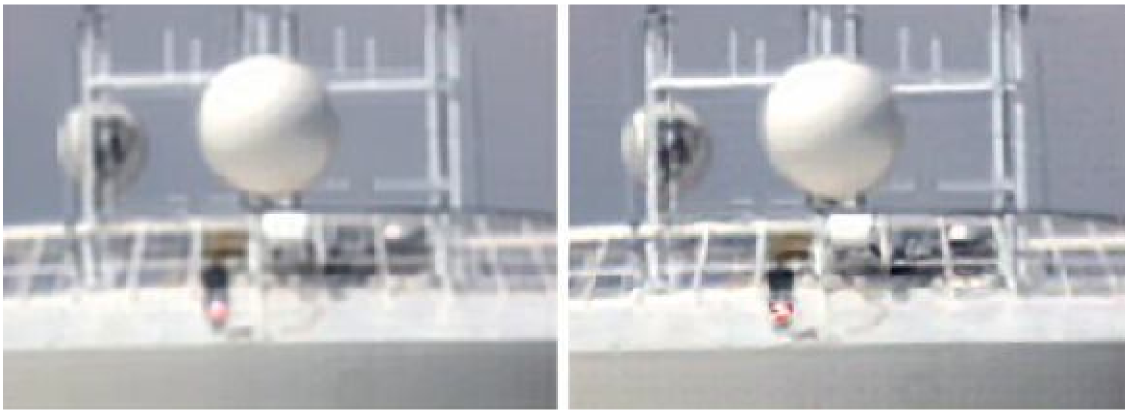

Figure 2: Blind Deconvolution applied to Figure 2 (Left) resulted the sharper image (Right)

III. PROPOSED ALGORITHM

The proposed algorithm is describe in below figure 3.It describe each step of algorithm

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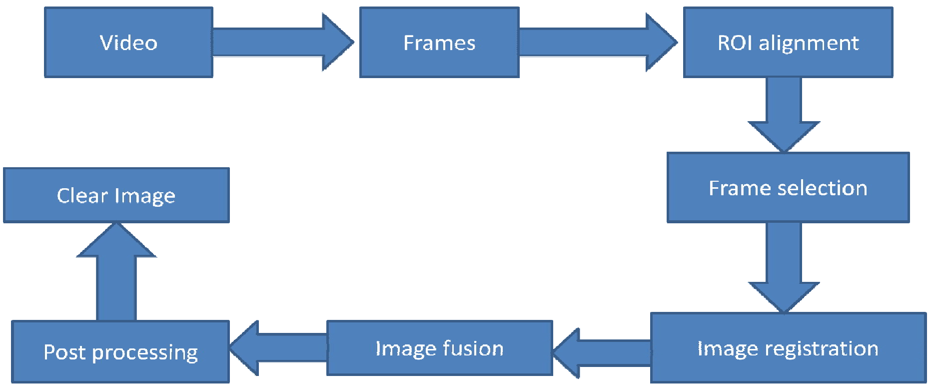

Fig 3: Block diagram of the proposed method

a. *Description of the Proposed Algorithm:*

Aim of Proposed method is to remove haze from the distorted video and finally get the restored image with maximum clarity. Algorithm consists of six steps.

Step 1: Load video from dataset:
Select video from dataset and process the rest of the steps on that video.

Step 2: Preprocessing:
Apply preprocessing method on video frames for removing initial blurrness.We applied here Gaussian filter for noise removal.

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Step 3: Alignment of Region of Interest:

Capturing video in the presence of atmospheric turbulence, especially when using high magnification lenses, may cause the ROI in each frame to become misaligned. High variation in the image is observed, due to camera movements.These variation significantly impact on image quality more than the turbulence. Morphological Image processing is used for the alignment of ROI. The ROI is marked in the first frame. The histogram, generated from the selected ROI and the surrounding area, is utilized to find an Otsu threshold which is used to convert the image to a binary map. An erosion process is then applied and the areas connected to the edge of image are removed. This step is done iteratively until the area near the ROI is isolated. Otsu threshold and the number of iterations are employed in other frames. The centre position of each mask is computed. If there is more than one isolated area, the area closest in size and location to the ROI in the first frame is used. Finally the centre of the mask in each frame is utilized to shift the ROI to align across the set of frames. Note that the frames with the incorrectly detected ROIs will be removed in the frame selection process. These frames are generally significantly different from others.

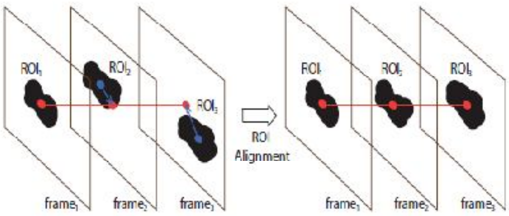

Figure 4: ROI alignment technique

Step 4: Frame Selection:

In our proposed method, not every frame in the sequence is used to restore the undistorted image since the bad images (e.g. the very blurred ones) would possibly deteriorate the fused result. A set of images are carefully selected using three factors; sharpness Gn, intensity similarity Sn and detected ROI size An. Gn can be computed from a summation of intensity gradients or the magnitude of high pass coefficients. Depending on these three factors the cost function is calculated with the formula-

$$C_n = \frac{w_G G_n}{\lambda_G + |G_n|} + \frac{w_S S_n}{\lambda_S + |S_n|} + \frac{w_A A_n}{\lambda_A + |A_n|}$$

Where Gn,Sn,An are three parameters. λ_G, λ_S, λ_A are calculated as sinemod function of Gn,Sn,An respectively.Lastly Wn,Ws,Wa are consider as constant equals to one.In this way the frame having maximum cost value are selected for fusion.Any two best frames will be selected for fusion.

Step 5: Image Fusion

We have adapted the region-based image fusion technique using complex wavelets proposed in to address the air-turbulence problem. The method first transforms each image into the DT-CWT domain. Then it employs an adapted version of the combined morphological spectral unsupervised image segmentation and a multiscale watershed segmentation to divide the image into R regions. The low pass DT-CWT coefficients of the fused image are simply constructed from the average of the lowpass values of all images, while the high pass coeffients are selected according to an activity measurement indicating the importance of that region. In this paper, to produce sharper results, we operate on each sub-band separately.

Step 6: Post Processing

In many cases, atmospherically degraded images also suffer from poor contrast due to severe haze or fog. In such cases, pre- or post-processing is needed to improve image quality. Numerous techniques have been proposed for haze reduction using single images. Here we employ a simple and fast method using contrast limited adaptive histogram equalization (CLAHE) and then haze removal is done. Haze removal is done by using dark channel prior mechanism.
Adaptive histogram equalisation is increases the contrast of image but dark channel prior method gives better result than histogram.In Dark channel prior method it checks the neighbour pixel and according to that it removes the haze from image and gives the haze free image with better clarity.

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IV. RESULTS ANALYSIS

Result analysis is done by two parameter Peak Signal to Noise Ratio and Mean Square Error.The image having higher PSNR and low MSE is having better quality than other images.By applying dark channel prior method the image having higher PSNR and Low MSE than the restored image obtained from method called CLEAR.In CLEAR method the adaptive histogram equalization is applied where as we are applying dark channel prior method which gives better result than CLEAR.

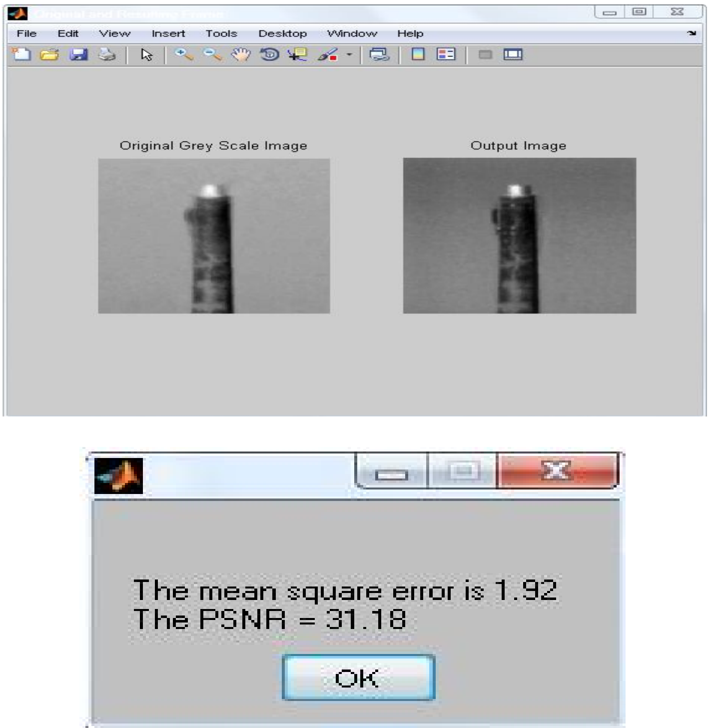

Figure 5: Quality assessment

V. CONCLUSION AND FUTURE WORK

This paper has introduced a new method for mollifying atmospheric instability in video surveillance system. The improvement of detecting an ROI in the image sequence is achieved using region-based fusion in the DT-CWT domain.We also propose a simple object alignment method and calculate a new cost funtion for frame selection to pre-process the distorted sequence. The process is completed with local contrast enhancement to remove haze interference called adaptive histogram. Haze removal is done by using dark channel prior mechanism. CLEAR offers class-leading performance for off-line extraction of enhanced static imagery.

Future Work:

- Finding out the advanced model, this can be used to enhance the video quality online.

More advanced models can be used to describe complicated phenomena, such as the sun's influence on the sky region, and the bluish hue near the horizon. I intend to investigate haze removal based on these models in the future.

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BIOGRAPHY

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