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DISTORTION VIDEO TO NOISELESS VIDEO USING DDDWT

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Abstract: **A variety of image restoration methods have been proposed that estimate an improved image by processing a sequence of images. Restoring a scene distorted by atmospheric turbulence is a challenging problem in video surveillance. Image registration enables the geometric alignment of two images and is widely used in various applications in the fields of remote sensing, medical imaging and computer vision. In this paper, we propose a novel method for mitigating the effects of atmospheric distortion on observed images. Region of interest (ROI) for each frame is taken, in order to extract accurate detail about objects behind the distorting layer. A simple and efficient frame selection method is proposed to select informative ROIs, only from good quality frames. Each ROI should be register in order to reduce the distortion. We solve the space varying distortion problem using region-level fusion based on the Double Density Dual Wavelet Transform (DDDWT).**

Keywords: **Double Density Dual tree wavelet transform (DDDWT), Image Registration, and Image Fusion.**

I. INTRODUCTION

Atmospheric turbulence is a naturally occurring phenomenon that can severely degrade the quality of long range surveillance video footage. Various types of atmospheric distortion can influence the visual quality of video signals during acquisition. Based on temperature variations to reduce the contrast and atmospheric turbulence, due to distortions include fog or haze. When the temperature difference between the ground and the air increases then the thickness of each layer decreases, In strong turbulence, not only scintillation, which produces small-scale intensity fluctuations in the scene and blurring effects are present in the video imagery, but also a shearing effect occurs and is perceived as different parts of objects moving in different directions. To interpret information behind the distorted layer, turbulence effects in the acquired imagery make it extremely difficult. Using various methods, there has been significant research activity attempting to faithfully reconstruct this useful information. In practice, the perfect solution is however impossible, since the problem is ill posed, despite being simply expressed with a matrix– vector multiplication as

$$I_{obv} = D\, I_{idl} + \varepsilon.$$

Here Iobv and Iidl are vectors containing the observed and ideal images, respectively. Matrix D represents geometric distortion and blur, while ε represents noise. Various approaches have attempted to solve this problem by modeling it as a point spread function (PSF). Where D is considered as a convolution matrix, and then applying de convolution with an iterative process to estimate Iidl. For the atmospheric distortion case, the PSF is generally unknown, so blind de convolution is employed. However, the results still exhibit artifacts since the PSF is usually assumed to be space-invariant.

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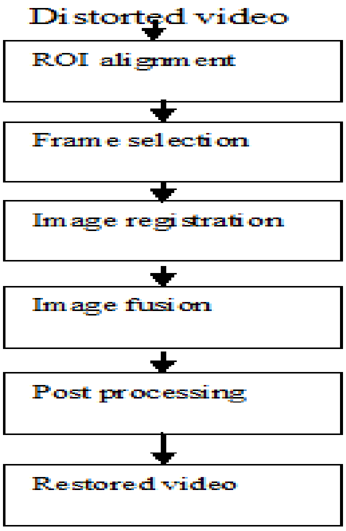


Fig.1. Block diagram of the proposed Method

1.1 Distorted Video:

One of the main visual effects is distortions due to atmospheric turbulence (known in the literature as "image or video dancing"). It may occur many other scenarios. For example, underwater imaging systems are subject to scattering effects and video shooting in summer suffers from hot air near the ground, and so on. Weak turbulence does not really affect human observers, but it can cause problems for an automatic target recognition algorithm because the shape of the object may be very different from those learned by some algorithms. Atmospheric turbulence in the air can often result in optical distortions that are visible in video acquired by cameras viewing scenes at long distances. This phenomenon can be observed, for Example, by looking at the cosmos through a telescope. The viewer observes planetary and stellar objects that appear to waiver. Another example of turbulence effects is the rippling wavy distortion that arises when observing a plane on a heated.

Fig.2. Distortion Video

II. PROPOSED METHOD

We propose a new fusion method for reducing the effects of atmospheric turbulence as depicted in Fig.2. Before taking the image fusion we are taking ROI from the frames and alignment them. Then frame selection is done by the sharpness, intensity similarity and ROI size. Non rigid Image registration is applied. We then employ a region-based scheme to perform fusion at the feature level. This has advantages over pixel-based processing since more intelligent semantic fusion rules can be considered based on actual features in the image, rather than on single or arbitrary groups of pixels.

The fusion is performed in the Double Density Dual Wavelet Transform (DDDWT) which employs two different real discrete wavelet transforms (DWT) to provide the real and imaginary parts of the CWT. Two fully decimated trees are produced, one for the odd samples and one for the even samples generated at the first level. This increases directional selectivity over the DT-CWT and is able to distinguish between positive and negative orientations giving six distinct sub-bands at each level, corresponding to ± 15°, ± 45°, ± 75°. Additionally, the phase of a DDDWT coefficient is robust to noise and temporal intensity variations thereby providing an efficient tool for removing distorting ripples. Finally, the DDDWT is near shift invariant an important property for this application. After fusion, the effect of haze is reduced using locally adaptive histogram equalization. Finally Contrast limited adaptive histogram equalization is applied.

A. ROI Alignment:

Capturing video in the presence of atmospheric turbulence, especially when using high magnification lenses, may cause the ROI in each frame to become misaligned. The displacement between the distorted objects in the successive frames may be too larger conventional image registration, using non rigid deformation, to cope with. Equally, matching using feature detection is not suitable nice strong gradients within each frame are randomly distorted spatially. Hence, an approach using morphological image processing is proposed. The ROI (or ROIs) is manually marked in the first frame. Then the histogram, generated from the selected ROI and the surrounding area, is employed to find an Otsu threshold which is used.

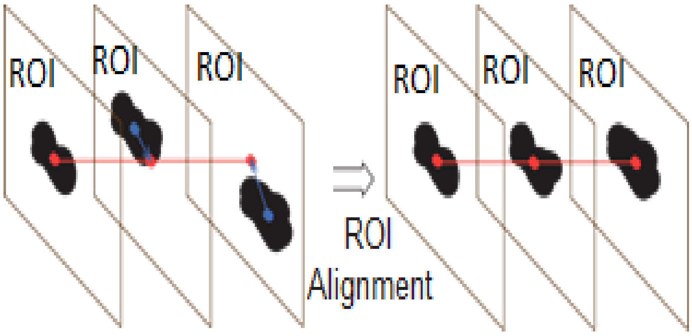
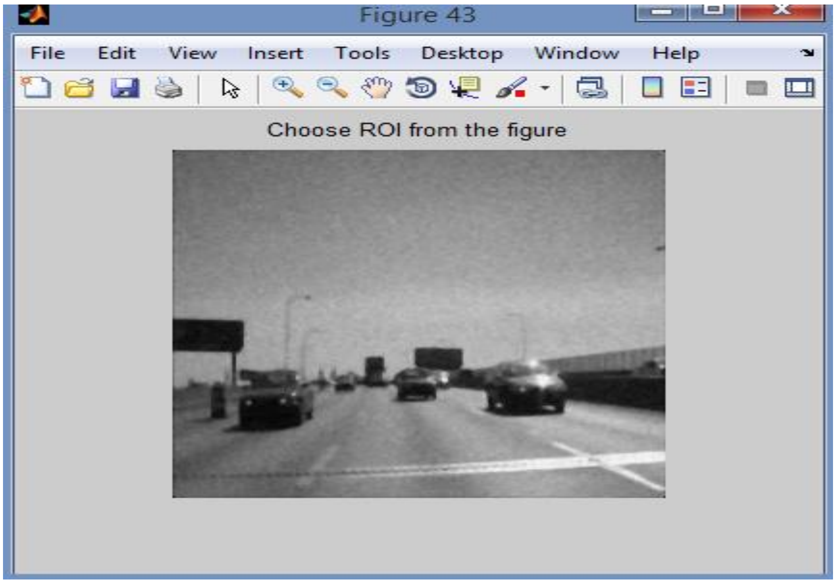
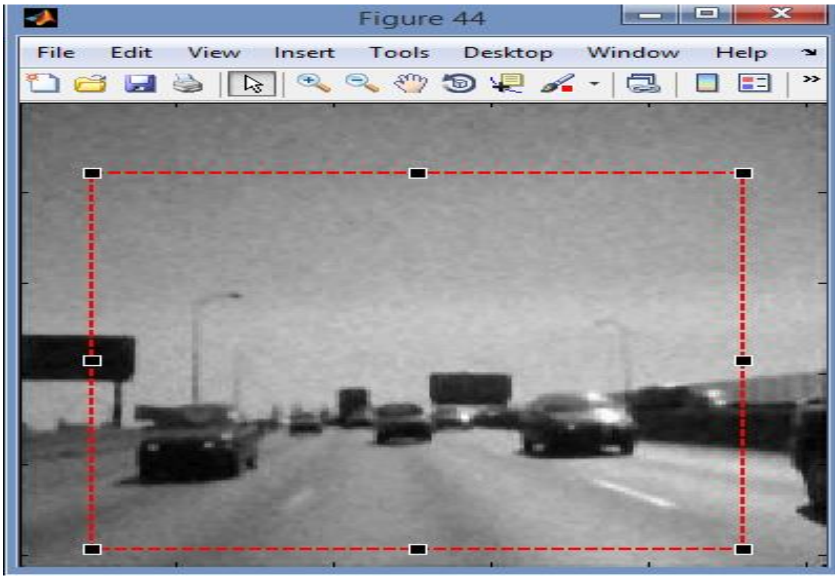


Fig.3. ROI Alignment technique to convert the image to a binary map

An erosion process is then applied and the areas connected to the edge of the sub-image are removed. This step is performed iteratively until the area near the ROI is isolated. The same Otsu threshold with the same number of iterations is employed in other frames. The centre position of each mask is then 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 and align it across the set of frames. Note that the frames with in correctly detected ROIs will be removed in the frame selection process. These frames are generally significantly different from others.





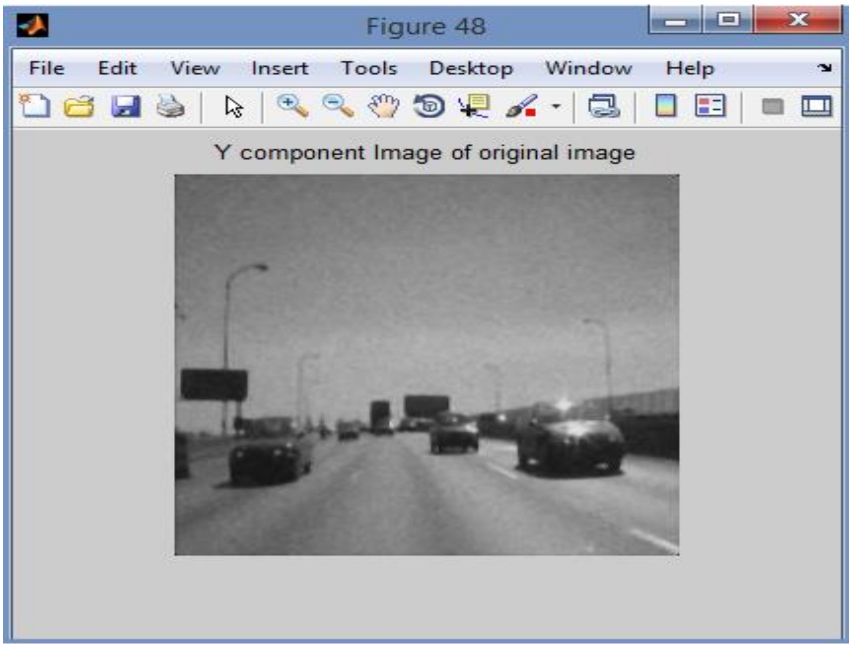


Fig.4.ROI alignment for each frame

B. Frame Selection:

In CLEAR, not all frames in the sequence are used to restore the image since the low quality frames (e.g. the very blurred ones) would possibly degrade the fused result. A subset of images is carefully selected using three factors: sharpness, intensity similarity and detected ROI size.

Sharpness Gn is one of the most important image quality factors since it determines the amount of detail an image can convey. Here, the sharpness parameter Gn is computed from the summation of the high pass coefficient magnitudes. Intensity gradients can also be used as the result is insignificantly different from high pass coefficients.

Intensity similarity Sn is employed to remove outliers. This operates under the assumption that most frames in the sequence contain fairly similar areas. Frames with significantly different content to others are likely to be greatly distorted. To compute Sn, the average frame of the whole sequence is used as a reference for calculating the mean square error (MSE) for frame n. Then MSE−1 represents the similarity of each frame.

Detected ROI size An is the total number of pixels contained in the ROI. This is used because, from observation, larger ROIs are likely to contain more useful information. The cost function Cn for frame n is computed using Eq.2

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

where wk and _k are the weight and slope control of the factor k 2 fG; S; Ag, respectively.

The sigmoid function is used here to prevent one factor dominating the others, e.g. a blocking are fact may cause significantly high values of sharpness, yet this frame should probably not be included in the selected data set. The k is set to equal the mean of factor k so that at the mean value, its cost value is 0.5. The cost Cn is ranked from high to low. The Otsu method can then be applied to find how many frames should be included in the selected set.

C. Image Registration:

Image registration is the process of overlaying two or more images of the same scene taken at different times, from different viewpoints, and/or by different sensors. It geometrically aligns two images the reference and sensed images. The present differences between images are introduced due to different imaging conditions. In this paper, Registration of non-rigid bodies using DDDWT, as proposed in, is employed. This algorithm is based on 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. Image registration has applications in remote sensing (cartography updating), and computer vision. In Medical images and It is also used in astrophotography to align images taken of space. Image registration is essential part of panoramic image creation.

D. Image Fusion:

Due to its shift invariance, orientation selectivity and multi scale Properties, the DDDWT is widely used in image fusion where useful information from a number of source images are selected and combined into a new image. We employ a region-based scheme in the DDDWT domain to implement image fusion at the feature level. The process is initialized using image segmentation to produce a set of homogeneous regions. Various properties of these regions can be calculated and used to determine which features from which images to include in the fused image. This has advantages over pixel based processing since more intelligent semantic fusion rules can be adopted based on actual features in the image, rather than on single or arbitrary groups of pixels. Lewis et al. Region-based fusion methods have been introduced by firstly segmenting N images individually or jointly. The segmentation map Sn of each image is down sampled by 2 to give a decimated segmentation map S;l n ;n 2 N of DRAFT MAY 2012 4 level l and sub-band _ of the DDDWT representation. For each region in each image n. Regions are then either chosen or discarded based on this priority and the fusion rule, to give the Wavelet coefficients of the fused image. A mask, M, is generated, where: The mask is the same size as that of the wavelet coefficient region in the fused image. The algorithm always chooses the region with the maximum priority to determine which image each of the coefficients representing a region, t, should come from. If Si 6= Sj , a segmentation map, SF , is created such that SF = S1 [S2 [: : : SN. Thus, where two regions ri;p and rj;q from image i and j overlap, both will be split into two regions, each with the same priority as the original. Finally, the fusion image is obtained by performing the inverse transform on the fused wavelet coefficients. In this paper, we have adapted the fusion technique explained above to address the air-turbulence problem. The low pass DDDWT coefficients of the fused image are simply constructed from the average of the low pass values of all registered images, while the high pass coefficients are selected according to an activity measure indicating the importance of that region. We employ an adapted version of O'Callaghan and Bull's joint morphological spectral unsupervised approach with multi scale watershed segmentation from to divide each image into similar regions, R. To produce sharper results, we operate on each sub-band separately. The priority P of region_ n 2 R in image n is computed with the detail coefficients d_; ln(x; y) of level l and sub-band _ as shown in, where __r _n__ is the size of such area used for normalization. The mask Mr._ is then generated from ranked priority to construct the fused image. The air-turbulence scenario differs from other image-fusion problems as the segmentation boundaries which separate inhomogeneous regions vary significantly from frame to frame (due to turbulence distortion). To provide the sharpest and most temporally consistent boundaries, for each region, we use the maximum of DDDWT coefficient magnitudes from all frames instead of selecting only one region based on P(r_ n). To each boundary map B_;l (constructed from the multi scale watershed segmentation approach for each sub band _ at level l), the dilation operation with a size of 1 pixel is applied. A 2D averaging filter is then applied to B;l to prevent discontinuity after combining neighboring areas.

III. RESULTS

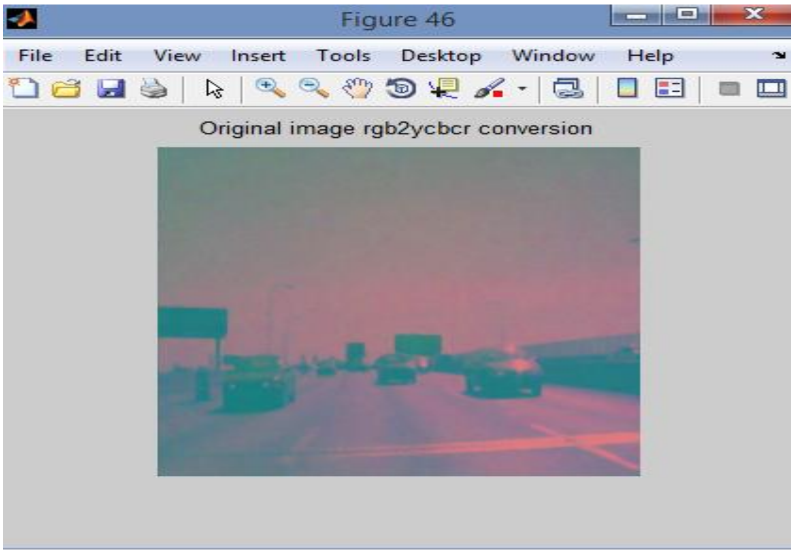


Fig.5 .rgb to cbr conversion

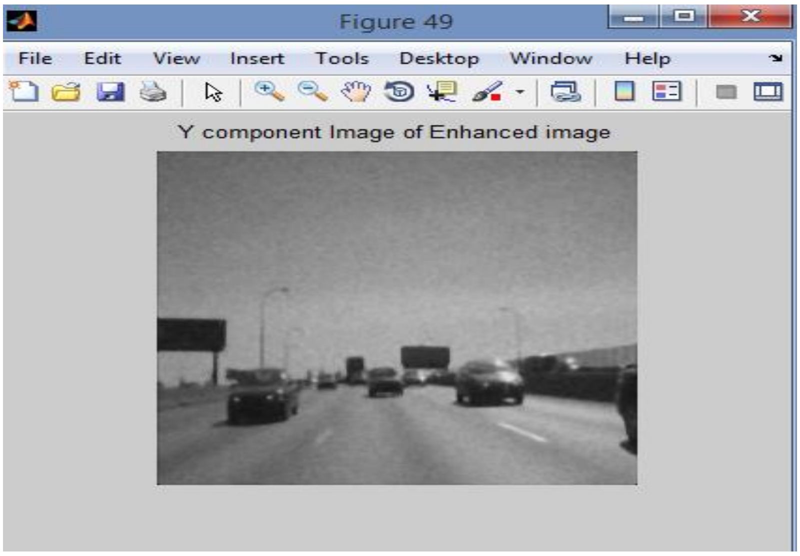


Fig.6. enhanced image

Fig.7. original image

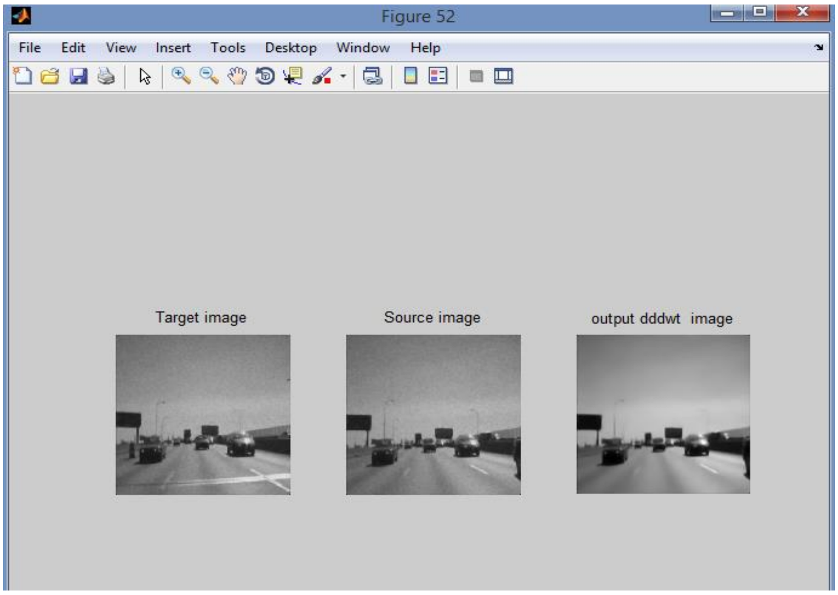


Fig.8. DDWT image

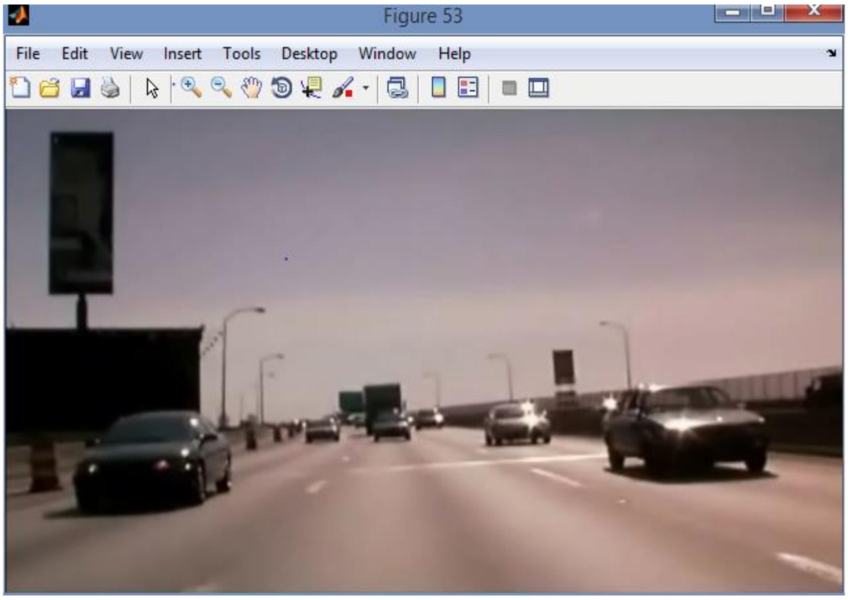


Fig.9. distortionless video

IV. CONCLUSION AND FUTURE WORK

In this paper, we have given a distorted video is given as a input and take a multi frame as a output and make the frame into video. We can use the full frame for processing the output. While processing the input image, first apply a frame selection using sharpness of the image, intensity of the image and size of the image and calculate the cost function with the help of this parameter. We can do fusion for two images, one as a reference image and another as the input image and we can fuse these two images to get the multi-frame as the output. Finally apply contrast enhancement in order to improve the quality of image. Significant improvements in image quality are achieved using region-based fusion in the DDDWT domain. The cost functions for frame selection to preprocess the distorted sequence. The process is completed with local contrast enhancement to reduce haze interference. From the distorted video we get the quality of the single frame for the ROI image.

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