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Allevation of Surveillance Video Using Complex Wavelet-Based Fusion

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ABSTRACT: Atmospheric turbulence is a challenging problem in video surveillance. This paper describes a new method for mitigating 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.

In order to extract accurate information from the distorting layer, a simple and efficient frame selection method is proposed to select informative ROIs only from good quality frames. The ROIs in each frame are then registered to further reduce offsets and distortions. We solve the space-varying distortion problem using region-level fusion based on the dual tree complex wavelet transform. Finally, contrast enhancement is applied. Again we applied an object alignment method for pre-processing the ROI since this can exhibit significant offsets and distortions between frames. The final step is Simple haze removal. The proposed method is shown to significantly better results than existing methods, providing enhanced situational awareness in a range of video surveillance scenarios. The video consist of many valuable information. As video signal are affected by some distortions such as fog haze etc. The in formations in the videos are extracted by using CLEAR Algorithm.

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

I.INTRODUCTION

The usage of surveillance videos in the open environments such as traffic signals is very important. The video signals may be affected due to some distortions such as fog haze etc.The information in the videos are extracted by using CLEAR. It consists of a series of steps to recover the information 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 the light**.**

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 . Examples of this effect are found at locations such as hot roads and deserts, as well as in the proximity of hot man-made objects such as aircraft jet exhausts. This is particularly a problem close to the ground in hot environments and can combine with other detrimental effects in long range surveillance applications, where images can be acquired over distances up to 20 km .Turbulence effects in the acquired imagery make it extremely difficult to interpret information behind the distorted layer. Hence, there has been significant research activity attempting to faithful reconstruct this useful information using various methods. In practice, the perfect solution is however impossible, since the problem is ill-posed, despite being simply expressed with a matrix–vector multiplication as -

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

where Iobv and Iidl are the observed and ideal images respectively., respectively. Matrix **D** represents geometric distortion and blur, while ε represents noise. Various approaches have attempted to solve this problem by using blind

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deconvolution (BD). It is obvious that using a single image is not sufficient to remove the visible ripples and waves, while utilizing 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. 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 . 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. In the Dual Tree Complex Wavelet Transform (DT-CWT) domain the fusion is performed as it provides near shift-invariance and directional selectivity. 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 metric, 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 dark channel prior method.

II. LITERATURE SURVEY

A. Atmospheric Turbulence and its Reduction

Since the turbulence in the captured images makes it difficult to interpret information behind the distorted 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, even though the represented equation of the problem can simply be written as Equation 1.

$$Iobv = DIidl + n \quad (1)$$

where Iobv and Iidl are the observed and ideal images respectively. D represents geometric distortion and blur, while n represents noise. Various approaches solve this problem by modeling it as a point spread function (PSF) and then employing deconvolution with an iterative process to estimate Iidl. For the heat haze case, the PSF is generally unknown, so blind deconvolution is sometimes employed. Some techniques however correct geometric distortion and deblurring separately.

A second problem that often accompanies turbulence is haze or fog. Using one observed image for enhancement can be applied to reduce fog interference, whereas it is accepted that multiple images are required for turbulence reduction. For example, contrast enhancement can be used to remove haze. It has been applied to distant areas in the image using a dark channel prior for single outdoor image haze removal. The dark channel prior is based on the statistics of haze-free outdoor images. They found that, in most of the local regions which do not cover the sky, pixels often contain have very low intensity in at least one colour (rgb) channel.

It is obvious that, when using only a single image, it is difficult to remove the visible ripples and waves caused by hot air turbulence. However, utilising a set of images to construct one enhanced image (reference image) makes more useful information available compared to using a single image. Current multi-frame methods that address the atmospheric turbulence problem are illustrated in Figure 1 either involving all functions or a subset of them.

The restoration process can be described by two main routes through the diagram. The first (green line) employs an image registration technique with deformation estimation. This process tries to align objects temporally to solve for small movements of the camera and temporal variations due to atmospheric refraction. The image fusion block may subsequently be employed in order to combine several aligned images. The other route (red line) employs image selection and fusion, known as `lucky region' techniques. These regions of the input frames that have the best quality in the temporal direction are selected.

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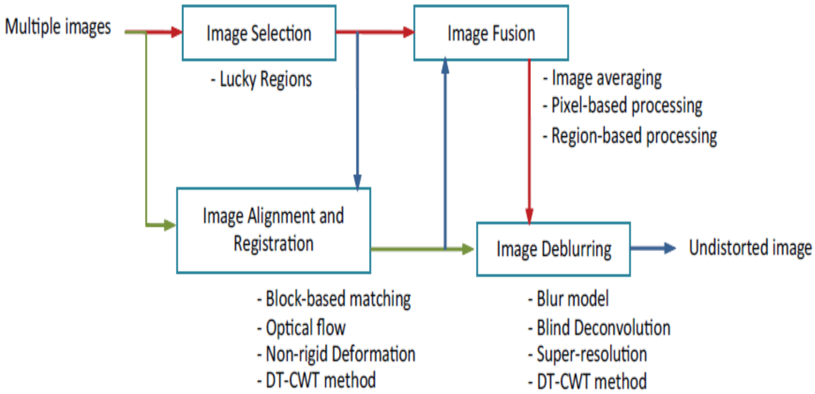

Fig 1: Image restoration diagram for atmospheric turbulence.

B. Image Selection

As heat haze causes the visible edges of an object to distort in time, multiple images captured with short exposure time are likely to show at least one correct edge. This leads to the technique called `Lucky imaging'.Lucky imaging techniques were originally introduced by Gregory in earth-based astronomic photography to overcome warping and blurring due to the atmosphere. The technique has been improved with the use of `Lucky regions' in order to apply to the heat haze problem at the photography taken at long horizontal path close to the ground where the distortions are space and time variant.

A quality metric is normally used to select the amount of each image included in the fusion operation. Traditional metrics use a sharpness measurement as this determines the amount of detail the image contains. Some examples include the maximal local gradient, the maximal local absolute difference (where the contrast is also used to average the absolute difference at the overall edge pixels), and eigen value sharpness. Sharpness can also be measured in the frequency domain.

C. Image Alignment and Registration

High-speed cameras can be used with short exposure time to freeze moving objects so as to minimize distortions associated with motion blur. However, a geometric distortion which is the result of anisoplanatic tip/tilt wavefront errors will still be present. Straightforward temporal averaging of a number of frames in the sequence can be used. Since atmospheric turbulence can be viewed as being quasi-periodic, averaging a number of frames would provide a reference frame that is geometrically improved, but blurred by an unknown PSF of the same size as the pixel motions due to the turbulence. A blind deconvolution algorithm can consequently be used to reduce the blur. This simple approach has been used in a speckle imaging technique.

The main drawbacks of this are that it requires a large number of frames to overcome the distortion and the average operation makes the deblurring process challenging. Moreover, unlike astronomic imaging, when imaging over a long horizontal path close to the ground, conditions are likely to be anisoplanatic and image dancing will affect local image displacements between consecutive frames rather than global shifts only. Therefore more sophisticated image alignment techniques are required.

D. Block-based Matching

Early work employed full-frame alignment, where camera translation and rotation are modeled by orthographic projection. This method does not give impressive results as the image always combines a variety of depths which have different translations. Also, to account for local isoplanatism, the image dancing affects local displacements. Hence, a local block-based has been proposed to solve this problem. This exploits the sum-of-squared differences (SSD) between each image and the averaged image, and the minimum value is selected from 5×5 neighbourhoods around the current pixel.A similar concept called locally operating Motion-Compensated Averaging (MCA) has been employed.

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The method utilizes Block Matching (BM) in order to identify and re-arrange uniformly displaced image parts. The local MCA-procedure has been used in both the lucky imaging and registration.

E Optical Flow

Optical ow is widely exploited in video processing. The Lukas-Kanade and HornSchunck methods can be applied to image registration in a coarse-to-fine iterative manner, in such a way that the spatial derivatives are first computed at a coarse scale (a smaller image) in a pyramid. The source image is warped by the computed deformation, and iterative updates are then conducted at successively finer scales. .

H. Image Deblurring

The final step of image reconstruction is image deblurring or sharpening. Here four key approaches are discussed in detail, a deconvolution from blur model, a blind-deconvolution, a super-resolution technique and deblurring using the DT-CWT.

1. Deconvolution from Blur Model

In the simple case it can be assumed that blur is global and known and therefore a deconvolution process can straightforwardly be applied. Several blur models for atmospheric turbulence suppression have been pre-defined, based on statistics studied by various researchers. In an astronomical imaging system this information can be gained from a wavefront sensor (WFS) which measures the distortion of the optical wavefront appearing at the telescope aperture. Performance for the case of terrain generated heat haze can be found in. However experimental studies in show that the choice of the kernel has an insignificant effect on the accuracy of estimation and therefore preference is given to the differentiable kernels with low computational complexity such as the Gaussian kernel. The specified Gaussian blur model is proposed by Hufnagel and Stanley.

$$H(u,v) = e^{-\lambda(u^2+v^2)^{\frac{5}{6}}}$$

where H represents the blur in the frequency domain and ʎ is estimated to match the blur present in the image. After obtaining the blur model, Wiener Deconvolution can be used. The Wiener filter is applied by calculating the 2D Fast Fourier Transform (FFT) of the input image, multiplying it by the Wiener filter and then taking the inverse FFT of the result. Alternatively an iterative deconvolution process, such as Richardson-Lucy, is widely employed. This converges to the maximum likelihood solution for Poisson statistics in the data. The method in claims that only 3-5 iterations are required to achieve the convergence. However the ill-posedness of the deconvolution problem makes it impossible to obtain perfect solutions. A spatially-variant solution should therefore be considered.

2. Blind Deconvolution

Classical deconvolution does not give impressive image restoration results when applied to shortexposure 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 Iobv is known, so Iidl 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 Iidl and Iobv, respectively. H is a square, block-circulant matrix of the blurring function. Using L2 norm, the x is estimated by minimisingıı Hx-yıı 2with a non-negativity constraint. The regularisation terms R and ʎ control the smoothness.

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3. Super-Resolution Methods

Alternative image deblurring techniques have been reported using image super-resolution. Here, super-resolution is defined formally as the removal of blur caused by a diffraction-limited optical system along with meaningful recovery of the object's spatial-frequency components outside the optical system's passband. A discrete sinc-interpolation is employed for image up sampling. If several pixels of different frames are to be placed in the same location in the output-enhanced frame, the median of those pixels is computed to avoid the inuence of outliers. The refinement process operates iteratively using the discrete Fourier transform (DFT) in order to reduce aliasing effects. Finally the result is down-sampled to the original resolution.

IV. METHODOLOGY

The proposed process is depicted in Fig 2. Details of each step are described below.

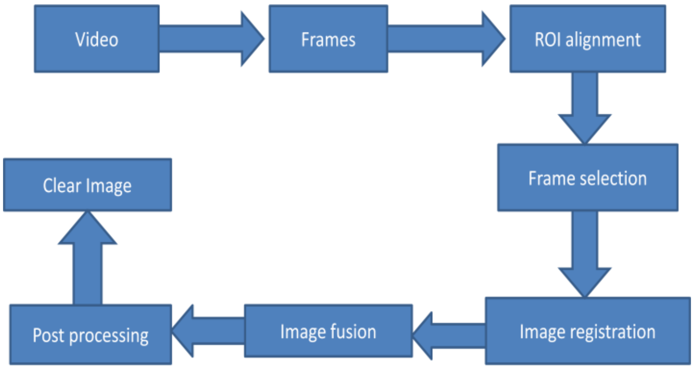

Fig 2: Block diagram of the proposed method

A. ROI Alignment

Object Alignment Shooting video in the far distance may cause the ROI in each frame to become misaligned. The interframe distance between the shaking objects may be too large to apply image registration. Unfortunately matching algorithms which use feature detection are not suitable for the traffic turbulence problem as strong gradients within each frame are distorted randomly. Here a simple approach using morphological image processing is proposed. 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. The same 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.

B . 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

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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 highpass coefficients..

C. Image Registration

Registration of non-rigid bodies using the phase-shift properties of the DT-CWT proposed in is employed in this paper. 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.

D. 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 lowpass 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.

E. 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.

VI. CONCLUSION

This paper has introduced a new method for mitigating atmospheric distortion in long range surveillance imaging. The improvement of visibility of 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 a new cost function for frame selection to pre-process the distorted sequence. The process is completed with local contrast enhancement to remove haze interference. The process is completed with local contrast enhancement and haze removal. Haze removal is done by using dark channel prior mechanism. CLEAR offers class-leading performance for off-line extraction of enhanced static imagery.

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