Dual-Tree Discrete-WT Based Turbulence Mitigation In Visual Surveillance

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Abstract- *Restoring a scene distorted by atmospheric turbulence is a challenging problem in video surveillance. The effect, caused by random, spatially varying, perturbations, makes model-based solution difficult and in most cases, impractical. In this paper, we propose a novel method for mitigating the effects of atmospheric distortion on observed images, particularly airborne turbulence which can severely degrade a region of interest (ROI). 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. 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. We further propose a learning-based metric specifically for image quality assessment in the presence of atmospheric distortion. This is capable of estimating quality in both full and no-reference scenarios. The proposed method is shown to significantly outperform existing methods, providing enhanced situational awareness in a range of surveillance scenarios.*

I. INTRODUCTION

Many types of atmospheric distortion shows the visual quality of video signal acquisition. Typical distortions include fog which reduce contrast, and atmospheric turbulence due to heat variations. In situations when the ground is hotter than the air above it, the air is heated and begins to form flat layers. When the temperature difference between the ground and the air increases, the thickness of each layer decreases and the air layers move upwards quickly, leading to faster and greater microscale changes in the air's refractive index.

This effect is clearly observed as a alter in the interference pattern of the light refraction. In turbulence, not only scintillation, which produces small-scale intensity fluctuations in the scene and blur effects are present in the video images, but also a shearing effect occurs and is perceived as different parts of things moving in various directions . Examples of this effect are found at locations such as hot roads and deserts, as well as in the nearness 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 observation applications, where images can be acquired over distances up to 20 km - 40kms.

Turbulence effects in the acquired imagery makes information behind the distorted layer. Hence, there has been significant research activity attempting to faithfully 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 in

$$\text{Iobv} = \text{DIidl} + \varepsilon$$

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), in which D is considered as a convolution matrix, and then employing de-convolution with an iterative process to estimate Iidl. For the atmospheric distortion case, the PSF is generally unknown, so blind deconvolution is employed [4]–[6]. However, the results still exhibit artifacts since the PSF is usually assumed to be space-invariant. It is understandable that removal of the visible patio-temporal distortions is not possible with a single image. Hence all methods utilize a set of images to construct one enhanced image. Current multi-frame methods that address this problem are illustrated in Fig. 1, where most approaches employ all functions or a subset of them. The restoration process can be described by two main routes through the diagram . The first (green dashed line) employs an image registration method with de-formation estimation. This process attempts to align objects temporally to solve for small movements of the camera and temporal variations due to atmospheric refraction. The image fusion block may optionally be employed (blue line) in order to combine several aligned images. Then, a de-blurring process is applied to the combined image (It is difficult since the blur is space - varying).

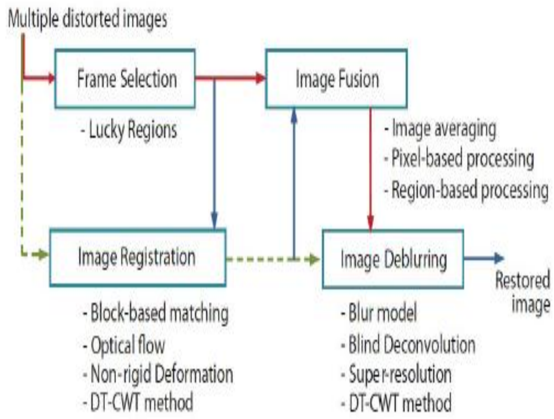

Fig. 1. Block diagram of image restoration for atmospheric turbulence.

III. PROPOSED SYSTEM

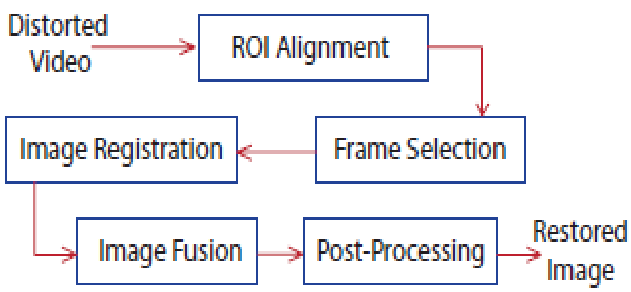

Fig. 2. Block diagram of the proposed method.

The technique has a new fusion method for sinking the effects of atmospheric turbulence as depicted in Fig. 2. First, before applying method, the combined images must be aligned. Here we introduce a new alignment approach for unclear images. As randomly distorted images do not provide identical features, we cannot use conventional methods to locate matching features. Instead, we apply a morphological image processing technique, namely erosion, to the ROI (or whole image) based only on the most informative frames. These are selected using a quality metric based on sharpness, intensity similarity and size of region of interest. Then, non-rigid image registration is applied.

IV. INTRODUCTION TO WAVELET AND WAVELET TRANSFORM

DUAL-TREE COMPLEX WAVELET TRANSFORM

The complex wavelet transform (CWT) is a complex-valued extension to the standard discrete wavelet transform (DWT). It is 2-D wavelet transform which provides multi resolution, sparse representation, and useful classification of the structure of an image. Further, it purveys a high degree of shift-invariance in its magnitude. However, a drawback to this transform is that it is exhibits 2^d (where d is the height of the signal being transformed) redundancy compared to a separable (DWT).In the area of computer vision, by exploiting the concept of visual contexts, one can quickly focus on candidate regions, where objects of interest may be found, and then compute additional features through the CWT for those regions only. These additional features, while not necessary for global regions, are useful in accurate detection and recognition of smaller objects.

The Dual-tree complex wavelet transform (DTCWT) calculates the complex transform of a signal using two separate DWT decompositions (tree *a* and tree *b*). If the filters used in one are specifically designed different from those in the other it is possible for one DWT to produce the real coefficients and the other the imaginary.

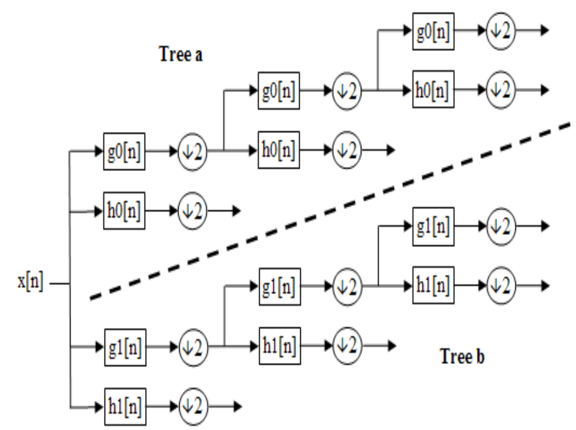

Fig:DWTdecompositions(tree *a* and tree *b*).

This redundancy of two provides extra information for analysis but at the expense of extra computational power. It also provides approximate shift-invariance (unlike the DWT) yet still allows perfect reconstruction of the signal. The design of the filters is particularly important for the transform to occur correctly and the necessary characteristics are:

- The low-pass filters in the two trees must differ by half a sample period
- Reconstruction filters are the reverse of analysis
- All filters from the same orthonormal set
- Tree *a* filters are the reverse of tree *b* filters
- Both trees have the same frequency response

IMAGE RESTORATION

The purpose of image restoration is to "compensate for" or "undo" defects which degrade an image. Degradation comes in many forms such as motion blur, noise, and camera misfocus. In cases like motion blur, it is possible to come up with an very good estimate of the actual blurring function of blur to restore the original image. In cases where the image is corrupted by noise, the best method which is implemented compensate for the degradation it caused. In this project Image restoration moves various directions is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques shearing effect occurs combined applications gives contrast stretching or de-blurring by a nearest neighbor procedure) provided by "Imaging packages" use no a priori model of the process that created the image. With image enhancement noise can effectively be removed by sacrificing some resolution, especially in the axial direction Removing noise Increasing contrast methods were described in two different versions.

I. Inverse Filter

In this method an image assuming a known blurring function. We will see that restoration is good when noise is not present and not so good when it is. If we know of or can create a good model of the blurring function that corrupted an image, the quickest and easiest way to restore that is by inverse filtering. Unfortunately, since the inverse filter is a form of high pass filer, inverse filtering responds very badly to any noise that is present in the frequency.

II. Weiner Filter

In this particular area implement image restoration using wiener filtering, which provides us with the optimal trade-off between de-noising and inverse filtering. We will see that the result is better than with straight inverse filtering. The inverse filtering is a restoration for deconvolution, when the image is blurred by a known low pass filter, it is possible of the image by inverse filtering or generalized inverse filtering. However, inverse filtering is very susceptible to additive noise. The approach of reducing one degradation at a time allows us to develop a restoration algorithm for each type of degradation and simply combine them. The Wiener filtering executes an optimal transaction between inverse filtering and noise smoothly surface.

III. Wavelet Restoration

Here to implement three wavelet based algorithms to restore the image. Although the Wiener filtering is the optimal tradeoff of inverse filtering and noise smoothing, in the case when the blurring filter is singular, the Wiener filtering actually amplify the noise. This suggests that a demising step is needed to remove the amplified noise. Wavelet-based denoising scheme, a successful approach introduced recently by Donohue, provides a natural technique for this purpose. Therefore, the image restoration contains two separate steps: Fourier-domain inverse filtering and wavelet-domain image denoising. The diagrammatic representation is shown below.

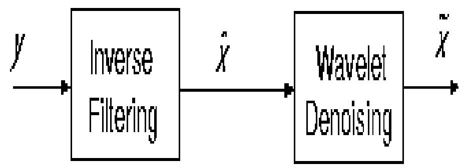

Fig: image restoration and denoising.

IV. Blind Deconvolution

In this restoring an image seems nothing very hard. There are direct methods for blind deconvolution as well as attempted only indirect methods, because they are less ad hoc. An example of a direct model lines normal to a suspected edge in the degraded image, and use this measurement for deconvolution. an additional indirect method tried no additive noise in the system. Thus, if our average blurring function goes to zero over many images, we can estimate our original frequency information as the geometric mean of the iteration were required for our approximations to holded images.

IMAGE QUALITY:

It is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems may introduce large amounts of distortion in the signal then the quality assessment is an important problem.

VI. SOFTWARE REQUIREMENTS

The fundamental devices needed for this task can be characterized into two general classes.

1) Hardware prerequisite,
2) Software prerequisite.

6.1HARDWAREREQUIREMENTS

In the hardware part a customary PC where MATLAB programming can be lived up to expectations is required, i.e. with a base system game plan of: RAM 1GB, hard circle and with a processor Pentium IV.

6.2 SOFTWAREREQUIREMENTS

In the item part MATLAB 2014a programming and the high light, which is to be settled, is the base need. A rate of the points of interest from MATLAB in highlight taking care of are:

- Easy to work with, as images are lattices.
- Built in capacities for complex operations and calculations (Ex. FFT, DCT and so forth…..).
- Images transforming tool kit,
- Support most picture configurations (.bmp,.jpg,.gip,tiff and so forth….)

VII. RESULTS

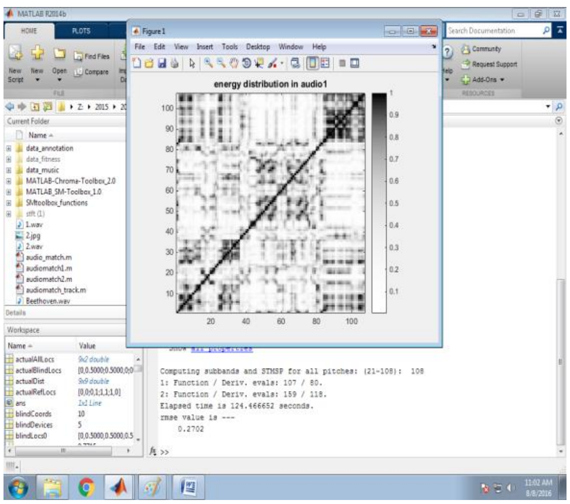

Fig.7.1 Energy distribution in audio1

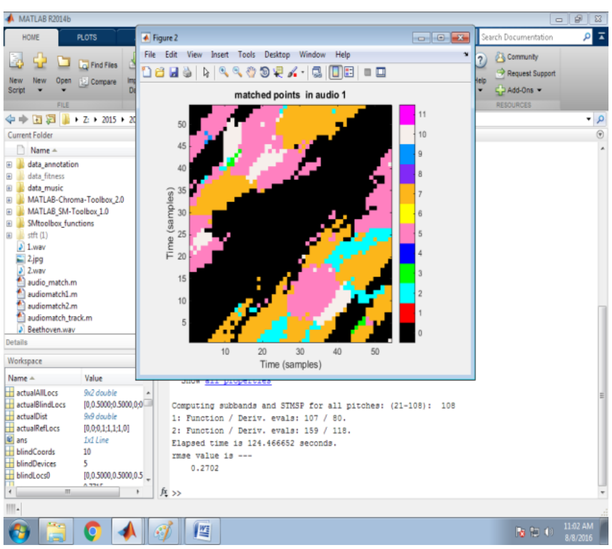

Fig.7.2 Matched points in audio1

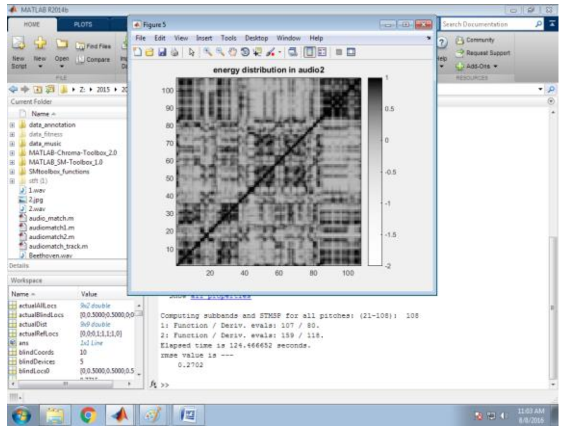

Fig.7.3 Energy distribution in audio 2

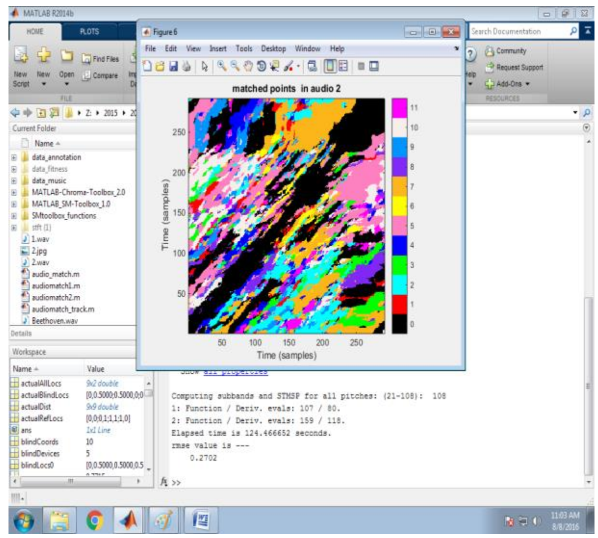

Fig.7.4 Matched points in audio 2

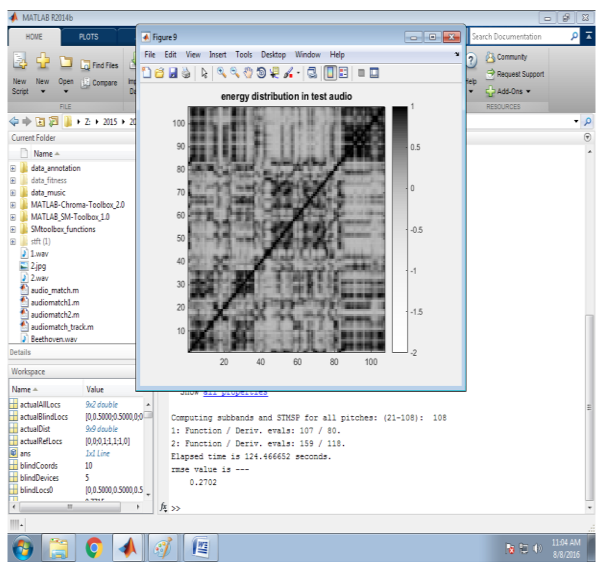

Fig 7.5 Energy Distribution in Test Audio

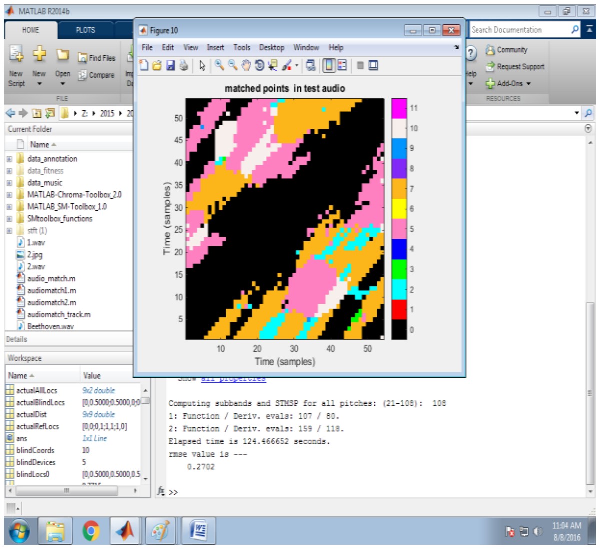

Fig 7.6.Matched Points in Test Audio

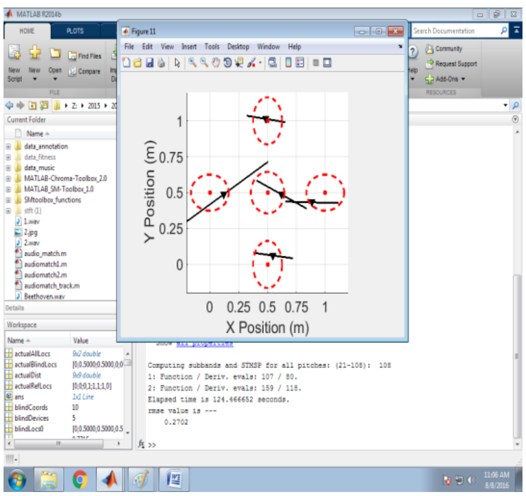

Fig.7.7 Device localization

VIII. CONCLUSION

The contribution of this paper is twofold. Firstly, we show that the Hilbert transformFIR approximation problem(12) can be expressed as an SDP problem and solved reliably. Secondly, we give a complete algorithm to compute the second filter bank of a dual-tree double-densityDWT. The algorithm comprises an initialization step based on SDP, followed by iterative refinement via nonlinear optimization. Design examples have shown the viability of this approach. We proposed double discrete wavelet transform—a novel analytical tool for blur processing. DDWT sparsifies the latent sharp image and blur kernel simultaneously using DWT. Sparse representation is key to decoupling blur and image signals, enabling blur kernel recovery and deblurring to occur in the wavelet domain. This framework also inspires a new generation of blur-tolerant recognition tasks aimed at exploiting the near-blur-invariant properties of DDWT coefficients. We validated the power of DDWT framework via example applications and experiments using real camera sensor data, but further development in blur kernel detection, deblurring, and recognition tasks are possible. Potential applications of DDWT include object velocity and defocus blur estimation, which are useful for making inferences on the object activities or the depths.

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