Atmospheric Turbulence Mitigation using Complex Wavelet-based Fusion

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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 a model-based solution dif cult 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 ef cient frame selection method is proposed to select informative ROIs only from goodquality frames. The ROIs in each frame are then registered to further reduce offsets and distortions. We solve the spacevarying distortion problem using region-level fusion based on the Dual Tree Complex Wavelet Transform (DT-CWT). Finally, haze removal is applied. We further propose a learning-based metric speci cally 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 clearly outperform existing methods, providing enhanced situational awareness in a range of surveillance scenarios.

Index Terms—image restoration, fusion, DT-CWT, quality metrics.

I. INTRODUCTION

ARIOUS 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 airborne contaminants. Atmospheric turbulence is sometimes referred to as scintillation or anisoplanatism. A variation in temperature causes different interference patterns in the light refraction, leading to unclear, unsharp, waving images of objects and other scene features. Examples of this effect are found at locations such as hot roads and deserts, as well 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.

Turbulence effects in the acquired imagery makes it extremely difficult to interpret information behind the distorted layer. Hence, there has been significant research activity attempting to faithfully reconstruct this useful information using various methods. The perfect solution however is, in practice, impossible since the problem is irreversible, despite being simply expressed as in Eq. 1.

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

$$I_{obv} = DI_{idl} + \varepsilon \tag{1}$$

Here I_{obv} and I_{idl} are the observed and ideal images respectively, D represents geometric distortion and blur, while ε represents noise. Various approaches have attempted to solve this problem by modelling it as a point spread function (PSF) and then employing deconvolution with an iterative process to estimate I_{idl} . For the atmospheric distortion case, the PSF is generally unknown, so blind deconvolution is employed [1]–[3]. The results, however, still exhibit artefacts since the PSF is usually assumed to be space-invariant.

It is obvious that removal of the visible ripples and waves is not possible with a single image. Hence all methods utilise 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 technique with deformation estimation [4]–[10]. 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 subsequently be employed in order to combine several aligned images. Then a deblurring process is applied to the combined image.

The other route (red solid line) employs image selection and fusion, often referred to as *lucky region*' techniques [11]–[17]. Those regions of the input frames that have the best quality in the temporal direction are selected. They are selected using an image quality metric, which is normally applied in the spatial frequency domain, to extract the best quality frames (minimally distorted and least blurred). These are then combined in an intelligent manner. Recently, this method has been improved by applying image alignment to those lucky regions [18]. Both approaches can be refined through

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a deblurring process (which is, again, a challenging problem as this blur is space-varying). Conventional registration methods are generally time-consuming, while conventional fusion approaches rely on a large number of short-exposure frames.

In this paper, we propose a new region-based fusion method to mitigate image distortion caused by air turbulence. The fusion is performed in the Dual Tree Complex Wavelet Transform (DT-CWT) domain since it provides near shiftinvariance and good directional selectivity [19]. We also propose novel frame selection and object alignment methods for pre-processing the ROI since this will frequently exhibit significant offsets and distortions between frames. Haze removal is used as the final step.

Our proposed algorithm is tested with real distorted sequences as well as with simulated sequences. The latter case includes heat distortion generated from gas burners and hence ground truth information is available. We also investigate a quality metric that is suitable for measuring restored image quality for atmospherically distorted content where genererally the ground truth is not available. Existing no-reference assessment (NR) methods [20]–[23] are tested with our simulated sequences. The results however do not show high correlation with the objective results. Therefore we introduce a new NR measure based on machine learning.

The remaining part of this paper is organised as follows. The proposed scheme for mitigating atmospheric distortion is described in detail in Section II. A test methodology for objective assessment is introduced in Section III. The performance of the method is evaluated on a set of images and is compared with other techniques in Section IV. Finally, Section V presents the conclusions of the paper.

II. PROPOSED MITIGATION SCHEME

We propose a new fusion method for reducing atmospheric turbulence as depicted in Fig. 2. First, before applying fusion, a subset of selected images or ROIs must be aligned. Here we introduce a new alignment approach for distorted images. As randomly distorted images do not provide identical features, we cannot use conventional methods to find matching features. Instead, we apply a morphological image processing technique 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 ROI size. Then, 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 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) 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 DWT and is able to distinguish between positive and negative orientations giving six distinct sub-bands at each level, corresponding to $\pm 15^\circ$, $\pm 45^\circ$, $\pm 75^\circ$. Additionally, the



Fig. 2. Block diagram of the proposed method



Fig. 3. Object alignment technique

phase of a DT-CWT coefficient is robust to noise and temporal intensity variations thereby providing an efficient tool for removing distorting ripples. Finally, the DT-CWT is nearshift invariant - an important property for this application. After fusion, haze is removed using locally-adaptive histogram equalisation.

For convenience, we refer to this algorithm as CLEAR (Complex waveLEt fusion for Atmospheric tuRbulence). Details of each step in our algorithm are described below.

A. Object Alignment

Capturing video at a distance in the presence of atmospheric turbulence, especially when using high magnification lenses, may cause the ROI in each frame to become misaligned. The inter-frame distance between the distorted objects may be too large to apply conventional image registration. Equally, matching using feature detection is not suitable since strong gradients within each frame are randomly distorted spatially. Hence, an approach using morphological image processing is proposed. The ROI (or ROIs) is marked in the first frame. Then the histogram, generated from the selected ROI and the surrounding area, is employed to find an Otsu threshold [24], 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 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 utilised to shift the ROI and align it across the set of frames (Fig. 3). Note that the frames with incorrectly detected ROIs will be removed in the frame selection process (section II-B). These frames are generally significantly different from others.

Fig. 4 demonstrates the improvement due to the proposed object alignment approach. The left image represents the



Fig. 4. Average frame of *Number Plate* sequence by (a) using 200 original frames, (b) using 50 frames most similar (lowest MSE) to (a), and (c) using 200 frames after applying object alignment approach.

average frame of the whole Number Plate sequence (see B4 in Table II and Fig. 9) and it reveals high variation due to camera movement. A simple alignment method might choose a subset of the original frames where the inter-frame distance is not too large. Fig. 4 (b) shows the example of this where, based on mean square error (MSE), 50 original frames with the smallest difference from the average image are selected. The alignment of these frames is consequently improved as shown by their average image in Fig. 4 (b). However, this truncation often leads to the loss of some useful information. In contrast, the proposed object alignment approach keeps all frames so that an intelligent approach can be employed later to select the best subset. The average frame of the whole sequence of our method is shown in Fig. 4 (c), which is clearer and sharper than the other two images (Fig. 4 (a) and (b)). This means that the aligned frames are more stable thereby producing better image registration results.

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 are carefully selected using three factors: sharpness, intensity similarity and detected ROI size.

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

- Intensity similarity S_n 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 S_n , 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** A_n 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 C_n for frame n is computed using Eq. 2.

$$C_n = \frac{w_G G_n}{\lambda_G + |G_n|} + \frac{w_S S_n}{\lambda_S + |S_n|} + \frac{w_A A_n}{\lambda_A + |A_n|}$$
(2)

where w_k and λ_k are the weight and slope control of the factor $k \in \{G, S, A\}$, respectively. The sigmoid function is used here



Fig. 5. The yz planes at column x=160 of each frame of *Number Plate*. Left: Distorted sequence corresponding to Fig. 4 (a). Top right: Aligned sequence corresponding to Fig. 4 (c). Bottom right: Registered sequence

to prevent one factor dominating the others, e.g. a blocking artefact may cause significantly high values of sharpness, yet this frame should probably not be included in the selected data set. The λ_k is set to equal the mean of factor k so that at the mean value, its cost value is 0.5. The cost C_n 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

Registration of non-rigid bodies using the phase-shift properties of the DT-CWT, as proposed in [25], 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. Fig. 5 show an improvement in temporal direction (z) of the *Number Plate* sequence after applying the proposed object alignment and image registration.

D. Image Fusion

Due to its shift invariance, orientation selectivity and multiscale properties, the DT-CWT is widely used in image fusion where useful information from a number of source images are selected and combined into a new image [26]-[28]. We employ a region-based scheme in the DT-CWT domain to implement image fusion at the feature level. The process is initialised using image segmentation to produce a set of homogeneous regions. Various properties of these regions can be caluculated and used to determine which features from which images to include in the fused image. This has advantages over pixelbased 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 [26], [27], [29]. The segmentation map S_n of each image is down sampled by 2 to give a decimated segmentation map $S_n^{\theta,l}, n \in N$ of level l and sub-band θ of the DT-CWT representation, where $\theta \in (1, \ldots, 6)$. If a list of all regions, T_n , of image n is $R_n = \{r_{n,1}, r_{n,2}, \ldots, r_{n,T_n}\}$, a multi-resolution priority map P_n is generated as

$$P_n = \left\{ p_{n,r_{n,1}}, p_{n,r_{n,2}}, \dots, p_{n,r_n,T_n} \right\}$$
(3)

for each region in each image n. Regions are then either chosen or discarded based on this priority and the fusion rule, ϕ , to give the wavelet coefficients of the fused image. A mask, M, is generated, where:

$$M_t = \phi(p_{1,t}, p_{2,t}, \dots, p_{N,t})$$
(4)

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 $S_i \neq S_j$, a segmentation map, S_F , is created such that $S_F = S_1 \cup S_2 \cup \ldots S_N$. Thus, where two regions $r_{i,p}$ and $r_{j,q}$ 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 lowpass DT-CWT coefficients of the fused image are simply constructed from the average of the lowpass values of all registered images, while the highpass 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 a multiscale watershed segmentation from [30] to divide each image into similar regions, R. To produce sharper results, we operate on each sub-band separately. The priority P of region $r_n^{\theta} \in R$ in image n is computed with the detail coefficients $d_n^{\theta,l}(x, y)$ of level l and sub-band θ as shown in Eq. 5, where $|r_n^{\theta}|$ is the size of such area used for normalisation. The mask $M_{r^{\theta}}$ is then generated from ranked priority to construct the fused image.

$$P(r_n^{\theta}) = \frac{1}{|r_n^{\theta}|} \sum_{l,(x,y) = r_n^{\theta}} \left| d_n^{\theta,l}(x,y) \right|$$
(5)

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 DT-CWT coefficient magnitudes from all frames instead of selecting only one region based on $P(r_n^{\theta})$. To each boundary map $B^{\theta,l}$ (constructed from the multiscale watershed segmentation approach for each subband θ at level l), the dilation operation with a size of 1 pixel is applied. A 2D averaging filter is then applied to $B^{\theta,l}$ to prevent discontinuity after combining neighbouring areas. The DT-CWT coefficients, $d^{\theta,l}$, of the fused image can be written as in Eq. 6. The example of $B^{\theta,l}$ is illustrated in Fig. 6 (Middle). The improvement can be seen by comparing images in Fig. 6



Fig. 6. Left: Traditional region-based fusion result. Middle: Mask $B^{\theta,l}$. Right: Enhanced result with the mask



Fig. 7. Fusion technique with phase adjustment shows improved result. Left: Fused image without phase adjustment. Right: Fused image with phase adjustment.

(Left) and Fig. 6 (Right). The enhanced result shows sharper edges without boosting noise in homogeneous areas.

$$d^{\theta,l} = (1 - B^{\theta,l}) \sum_{R} M_{r^{\theta}}(d_{1}^{\theta,l}, d_{2}^{\theta,l}, \dots, d_{N}^{\theta,l}) + B^{\theta,l} \max(d_{1}^{\theta,l}, d_{2}^{\theta,l}, \dots, d_{N}^{\theta,l})$$
(6)

To reduce the distortion due to rippling, the phase of the complex wavelet coefficients play an important role since it corresponds to the precise location of directional features in its support regions. Hence, the DT-CWT coefficients, $d^{\theta,l}(x,y)$, of the fused image are adjusted with a unit vector representing the average phase from all frames, N, used in the fusion process (Eq. 7). The average phase can be used because, in turbulent motion, pixels deviate from their actual positions with approximately zero mean and with a quasi-periodic motion [7]. The improvement of the fusion result is demonstrated in Fig. 7. Clearly, the image with adjusted phases produces straighter lines which are obviously closer to the truth in this case.

$$\tilde{d}^{\theta,l}(x,y) = \frac{\sum_{n=1}^{N} d_{n}^{\theta,l}(x,y)}{\left|\sum_{n=1}^{N} d_{n}^{\theta,l}(x,y)\right|} \left|d^{\theta,l}(x,y)\right|$$
(7)

To reduce noise, we apply a shrinkage function, A_s , derived as Maximum A Posteriori (MAP) estimators as in [31], [32]. Then, if sharpening is required, a gain $A_g > 1$ can be applied to boost highpass-coefficient magnitudes. However, this simple technique might cause any remaining noise to become clearly visible. Hence we enhance only those high-pass coefficients where they form regions of large magnitude. We create the binary map $Q^{\theta,l}$ for each subband, in which $Q^{\theta,l} = 1$ if $|d^{\theta,l}| > \tau$, where τ is a predefined threshold. Isolated pixels are subsequently removed from $Q^{\theta,l}$. The modified highpass coefficients are finally rewritten as Eq. 8.

0

$$l^{\theta,l} = \left(A_g^{\theta,l}Q^{\theta,l} + (1-Q^{\theta,l})\right)A_s^{\theta,l}\tilde{d}^{\theta,l} \tag{8}$$



Fig. 8. Original image (left) and its contrast enhancement with global HE (middle) and CLAHE (right)

E. Post Processing

1) Haze Removal: A problem that often accompanies turbulence is haze. Simple and fast methods such as histogram equalisation (HE) can be used to reduce this effect. However, since we consider the ROI and the meaning it carries, a contrast limited adaptive histogram equalisation (CLAHE) is more suitable than global adjustment. The method calculates local histograms derived from a neighbourhood region. A threshold is predefined to limit the cumulative values thereby preventing overamplifying small amounts of noise in largely homogeneous regions. An example of haze removal with HE and CLAHE is shown in Fig. 8. The number at the top of the car is much clearer in the CLAHE result.

2) Image sharpening: Generally the embedded parameter A_g in our approach produces sharp results; however, in cases which are out-of-focus or which lack a *lucky region*', post-processing may be required to further sharpen the images. A number of sharpening methods exist, such as [33], [34]. However, if the constituent images are very poor, it is almost impossible to obtain a sharp result. Moreover, it may exhibit a halo effect due to over sharpening.

III. QUALITY ASSESSMENT

Image quality assessment measures perceived image degradation, typically compared to an ideal or perfect image and is important when assessing the performance of individual systems or for ranking different solutions. Objective image quality metrics can be classified according to the availability of a reference (distortion-free) image, with which the distorted image is to be compared. Most existing approaches are classed as full-reference (FR), meaning that a complete reference image is available. When a reference is not available, as is often the case for heat haze reduction, quality assessment becomes challenging, and is referred to as no-reference (NR) or blind quality assessment. Methods cited in the literature are usually based on the prior knowledge of the distortion characteristics and none are derived from spatially varying distortions. We therefore propose a new NR metric for the atmospheric turbulence scenario.

A. Full-Reference Image Quality Assessment

The most commonly used FR method is Peak Signal to Noise Ratio (PSNR) - based on Mean Squared Error (MSE). Such distortion-based metrics are simple to implement, but do not always give a good indication of perceptual fidelity. Structured information is an important factor in human visual perception and metrics such as Structural Similarity (SSIM) [35] have been introduced to reflect this. SSIM shows significant correlation with subjective mean opinion scores compared with PSNR and an extended version, Multiscale Structural similarity (MS-SSIM) [36], provides more flexibility in incorporating the variations of image resolution and viewing conditions. Natural scene statistics (NSS) are used in in the Visual Information Fidelity (VIF) metric to model a distortion information shared between the test and the reference images [37]. Human Visual System (HVS) related knowledge is also employed in a wavelet-based method, Visual SNR (VSNR) [38]. Finally, a perception-based image model (PIM) was proposed in [39] using noticeable differences based on local spatial frequency energy to measure video quality.

B. No-Reference Image Quality Assessment

The JPEG quality score was one of the first NR quality assessment methods introduced. It attempts to align image quality with HVS perception by characterising blockiness and blurring [20]. Subsequently, the JPEG2000 (JP2K) score was proposed for blind assessment of images compressed by wavelet based coding [21]. The Anisotropic Quality Index (AQI) is another NR metric based on measuring the variance of the expected entropy of a given image in a set of predefined directions [22]. Recently, the combination of five distortion types, namely JPEG, JPEG2000, white noise, Gaussian blur and fast fading, were used in the Blind Image Quality Index (BIQI) [23].

C. Proposed NR Method for Atmospheric Distortion

Since none of the existing methods described above work well with atmospheric distortion, in this paper, we introduce a new blind image quality assessment metric specifically for this scenario. We employ support vector regression (SVR) [40] to model and predict image quality scores using the features listed in Table I. There are three groups of features:

- **Individual scale** The magnitude of highpass coefficients relate to details and sharpness of the image, while the phase can be linked to edge information. We therefore employ the mean and variance of both values to compute the feature vectors at each scale level. We decompose the image into 3 levels using the DT-CWT.

- Inter-scale Weighted mean and variance at level l are computed using the magnitudes of the next coarse level to calculate a weight as shown in Eq. 9. Here $\hat{d}^{\theta,l} \in \hat{D}^l$ is the upsampled version of $d^{\theta,l}$ by 2 so that $\hat{d}^{\theta,l}$ has the same size as $d^{\theta,l-1}$. The weighted mean is computed as shown in Eq. 10, where $\kappa^{\theta,l}$ is the magnitude or the phase of complex coefficient $d^{\theta,l}$. The weighted variance is calculated from all $\kappa^{\theta,l}(x,y)$ that have $w^{\theta,l}(x,y) > 0.1$. This follows the assumption that the coefficients adjacent to strong edges (high $|d^{\theta,l}|$) are more important, since the distortions in those areas affect human perception more than others. Moreover, atmospheric turbulence consistently manifests itself as clear visible ripples along object edges.

 TABLE I

 Features for modelling the quality of the images distorted by atmospheric turbulence

dimension
(3 scales)
6
6
4
4
2
4



(a) Simulated datasets (A1-A8)

$$w^{\theta,l}(x,y) = \frac{\left|\hat{d}^{\theta,l+1}(x,y)\right|}{\sum_{\theta,(x,y)} \left|\hat{d}^{\theta,l+1}(x,y)\right|}$$
(9)

$$S_{\kappa}^{l} = \sum_{\theta, (x,y)} w^{\theta,l}(x,y) \cdot \kappa^{\theta,l}(x,y)$$
(10)

We also utilise entropy to measure the randomness of the phase in the vicinity of strong edges, since the higher phase randomness can imply more ripples. We employ the weighted average formula in Eq. 9 and 10 to compute entropy features. Here $\kappa^{\theta,l}(x,y)$ represents local entropy at position (x,y) calculated in a 5-by-5 neighbourhood.

- **Existing NR methods** Existing NR scores are also included to model image quality, since they are derived for general natural images.

The SVR parameters are selected by cross validation. As the number of features is not large, principal component analysis is not required for dimensionality reduction. Instead, we have directly tried with combinations of different subsets of features and have found that the combination of all features performs best. We refer to this new metric as QSVR.

IV. RESULTS AND DISCUSSIONS

First, we examine which NR methods (section III-B) are suitable for the turbulence case. Measurement values are compared with the FR methods (section III-A). Then the selected metrics are used to assess the results of our proposed atmospheric turbulence mitigation and to compare with the existing methods.

A. Quality Metric Selection

We generated a body of images containing objects distorted by heat haze using a number of gas hobs. The flow of gas created temperature gradients leading to distortions in the scene. We captured 8 sequences containing different objects, including faces, common objects and text. The distortions in each video were varied by altering the gas flow to produce three classes referred to as low, medium and high distortion with 100 frames each. Frames from each sequence are shown in Fig. 9 (a) and were used to investigate the performance of the NR methods.



(b) Real datasets without ground truth (B1-B6)

Fig. 9. Distorted sequences. (a) Simulated datasets generated from gas burners. (b) Real datasets.

The dataset of each sequence was divided into training and validation sets randomly. As subjective scores for these sequences did not exist, we attempt to find the NR metric that achieves the highest correlation with the FR scores. The values of the FR and the NR approaches are computed and normalised so that the measured qualities span 0 and 1 for better comparison. The performance of the NR methods is also assessed according to the correlation with the average of the FR scores. Fig. 10 shows the average correlation value for the 8 sequences using three statistical parameters: Linear Correlation Coefficient (LCC), Spearman Rank Order Correlations Coefficient (SROCC) and Root Mean Squared Error (RMSE). It can be concluded that only JP2K, AQI and our QSVR are suitable for the air turbulence problem. The JPEG method is not well matched to our problem since it emphasises blocking artefacts. BIQI is also based on distortions present in compressed data rather than atmospheric distortions. It can be clearly seen from Fig. 10 that QSVR outperforms all other NR methods.

B. Still Image Results

CLEAR has been tested using the three datasets summarised in Table II. The first set (A1-A8) contains the simulated data described in section IV-A (Fig. 9 (a)), while the other two datasets include real effects of turbulence in long range imaging. These real datasets have been captured without



Fig. 10. Correlation comparison between NR methods

TABLE II DISTORTED SEQUENCES

type	#	name	colour type	resolution	# frames
	A1	Books	RGB	1024×1024	100
	A2	Barcode	RGB	512×256	100
	A3	Back Car	RGB	256×256	100
Simulated	A4	Faces	RGB	512×512	100
datasets	A5	Boxes	RGB	320×240	100
	A6	Plant	RGB	512×512	100
	A7	Front Car	RGB	512×512	100
	A8	Toys	RGB	1200×800	100
	B1	Hill House	grey	512×512	75
D 114	B2	Hot Road	grey	320×240	175
Real datasets	B3	Cold Car	RGB	720×576	75
without	B4	Number Plate	RGB	320×240	200
ground truth	B5	Monument	RGB	512×512	100
	B6	Mirage	RGB	256×256	50
Real datasets	C1	Chimney	grey	237×237	100
with ground	C2	Building	grey	237×237	100
truth [4]	C3	Books	grey	109×109	100

Note that sequences B5 and B6 can be downloaded from www.bristol.ac.uk/vi-lab.

ground truth (B1-B6) and with ground truth (C1-C3) as shown in Fig. 9 (b) and Fig. 14 (first row), respectively.

In the case of colour sequences, the images are converted into YC_bC_r colour space and only the greyscale channel (Y) is processed. The output colour channels (C_b and C_r) are generated using the average values of all selected registered frames. This simple technique can be applied successfully because the distortions of the colours have less influence on human vision perception. At the end of the process, the grayscale fusion result is combined with the colour channels and converted back to the original colour space.

The parameters used in our experiments are as follows. The DT-CWT is applied with 3 or 4 decomposition levels when the image resolution is smaller or larger than 128×128 pixels, respectively. The weights for the frame selection w_G , w_S and w_A are set to 1. The value τ for cleaning the map $Q^{\theta,l}$ is individually set for each subband in each level to $\tau^{\theta,l} = \overline{|d|}^{\theta,l} + 0.5 \sigma^{\theta,l}$, where $\overline{|d|}^{\theta,l}$ and $\sigma^{\theta,l}$ are the mean and the standard deviation of the magnitude of the highpass subband. The gains $A_g^{\theta,l}$ are equal for each subband at the same level and are 2.5, 1.8, 1.2 and 1 for l = 1, 2, 3 and 4, respectively. For CLAHE, a window of 8×8 pixels is used to compute local histograms which are clipped at 1%.

1) Simulated datasets: The sequences generated with gas burner turbulence (Fig. 9 (a)) are used to compare the perfor-



Fig. 11. Performance comparison between SVOLA and CLEAR using: Left: FR methods, Right: NR methods.

mance of CLEAR with that of Shan's Blind Deconvolution (BD) [41] and with the space-variant overlap-add method (SVOLA) by Hirsch *et al.* [4]. In this case, the FR image quality assessment can be used. Fig. 11 shows the performance of the proposed scheme, BD and SVOLA applied to the *Toys* and *Plant* sequences. The blind quality assessments (SVR and AQI) are also computed to demonstrate the correlation between FR and NR methods.

2) Real datasets without ground truth: The six sequences (B1-B6) captured at long range exhibiting significant turbulence distortions (Fig. 9 (b)) are used here. The Number Plate, *Mirage* and *Monument* sequences show a significant shift of the ROI area between frames, so we have also artificially applied spatial shifts of between 1-20 pixels randomly to the other sequences. It is important to note that, in our comparisons with BD and SVOLA, these two methods have been applied to, and benefit from, the object alignment, frame selection and registration methods used in CLEAR. If BD and SVOLA are applied without this, there results are significantly inferior. Despite this benefit, the reconstructed images shown in Fig. 12 and Fig. 13 show that CLEAR can restore better detail and more easily readable text.

The objective results shown in Table III support the subjective results. The proposed fusion approach achieves better JP2K, AQI and QSVR scores for all distorted sequences, apart from *Number Plate* where the AQI value of SVOLA is slightly better (probably insignificant: $0.003 \approx 0.092$ %) than CLEAR. However, referring to Fig.12 the subjective result of the *Number Plate* using the proposed approach reveals more readable numbers. It should be noted that this sequence is highly distorted and the number on the plate is impossible to read in any single frame. It should be further noted that the quality values calculated from the whole frame are slightly different from those in Table III, which relate solely to the ROI.

The subjective results clearly show that the CLEAR algorithm removes atmospheric distortion more efficiently than the



Fig. 12. Reconstructed images from real sequences (B1-B5). Left: Shan's BD [41]. Middle: SVOLA [4]. Right: CLEAR. It should be noted that SVOLA and BD results have benefited from CLEAR's selection and registration processes.

other approaches. Shan's BD is inefficient for air turbulence since the PSF is assumed to be similar for the entire image, while our method processes sets of homogeneous regions separately. Shan's method also takes four times longer to process than our proposed method, mainly to estimate the PSF. SVOLA subdivides an image into overlapped regions and estimates the PSF separately; as a result, it provides better results compared to Shan's method. However the computation time is even longer and the results are not as sharp as the proposed method. In addition, prior knowledge of PSF size is required for both previous methods.

3) Real datasets with ground truth: Three sequences, Chimney, Books and Building have been made available with



Fig. 13. *Mirage* sequence (B6). Top-left: Magnified number plates of (from top) original frame, SVOLA, CLEAR and undistorted frames captured at closer distance). Top-right: Original image. Bottom-left: Result of SVOLA . Bottom-right: Result of CLEAR. Again it should be noted that BD and SVOLA results use CLEAR's preprocessing.

TABLE III Objective results using NR methods

sequence	method	JPEG	BIQI	JP2K	AQI	QSVR
Hill House	BD	10.07	2.22	52.61	2.13	54.32
	SVOLA	11.15	2.04	51.35	2.22	56.12
	CLEAR	11.05	2.24	61.71	2.99	56.88
Hot Road	BD	8.11	2.42	78.70	2.41	47.77
	SVOLA	9.25	4.09	78.43	2.56	47.81
	CLEAR	10.04	3.28	78.77	3.18	48.72
Cold Car	BD	9.02	1.87	58.40	0.16	42.26
	SVOLA	9.95	2.04	59.85	0.09	42.62
	CLEAR	10.44	2.57	62.93	1.50	43.70
Number Plate	BD	8.21	3.62	68.62	2.00	42.29
	SVOLA	8.99	3.21	58.79	3.26	42.75
	CLEAR	10.36	3.25	78.49	3.26	43.15
Mirage	BD	7.91	2.59	65.32	8.12	41.73
	SVOLA	10.64	3.99	66.83	9.39	42.49
	CLEAR	10.83	4.20	73.83	11.77	43.19
Monument	BD	8.65	2.47	72.84	0.88	45.23
	SVOLA	9.14	3.39	79.65	1.94	47.81
	CLEAR	9.93	3.32	79.98	3.44	48.13

their ground truth by Hirsch [4]. Also, the results from their approach are available. The results are also compared to another atmospheric turbulence removal approach from Zhu [10]. The subjective and objective results for these sequences are shown in Fig. 14 and Table IV, respectively. The PSNR, MS-SSIM, VSNR and PIM values reveal that CLEAR outperforms SVOLA and Zhu's approach, but the VIF value is highest for SVOLA. Interestingly, the subjective results shown in Fig. 14



Fig. 14. Hirsch's Data (C1-C3). Top-Bottom: Original frame, Ground truth, SVOLA's results, ZHU's results and CLEAR's results

reveal that our results are the most similar to the ground truth. The results of Zhus fusion appear sharpened around structural features, but lose texture in homogenous areas thereby yielding the lowest objective scores.

C. Results for Sequences Containing Moving Objects

This test was investigated in order to show the potential of the proposed algorithm when applied to video containing moving objects. Here, part of the moving object is selected as the ROI. A number of forward and backward frames are stored in a reference buffer. The forward frames are the future video frames, while the backward frames are the reconstructed frames using the proposed fusion process. The ROI of all frames in the buffer are aligned to the ROI of the current frame using the proposed object alignment method. Then, they are registered to their average. Subsequently, these registered frames are fused using the proposed method to

TABLE IV Objective results using FR methods

sequence	method	PSNR	MS-SSIM	VSNR	VIF	PIM
Chimney	SVOLA	31.93	0.96	11.19	0.21	35.25
	ZHU	28.90	0.95	10.60	0.13	33.29
	CLEAR	32.02	0.96	12.98	0.19	35.58
Building	SVOLA	24.88	0.88	6.52	0.33	31.03
	ZHU	23.83	0.87	5.89	0.24	30.47
	CLEAR	25.18	0.91	6.95	0.26	31.34
Books	SVOLA	19.39	0.83	8.61	0.43	32.11
	ZHU	20.34	0.85	8.59	0.35	32.12
	CLEAR	25.36	0.94	10.58	0.39	32.57



Fig. 15. The *Wine* sequence. Top: from distorted video. Bottom: from reconstructed video. Left: the ROI of the 5th frame showing the barcode area which includes the row (y) of the middle pictures . The xz planes (z=temporal direction). Middle: at y=200. Right: at y=100.

remove distortions. Using the reconstructed frames as one of the references can lead to error accumulation over long time periods. Therefore, periodic refresh of the reference buffer is required. Fig. 15 shows parts of the *Wine* sequence where the wine bottle is moved from the right to the left of the display over time. The online process employs two forward and two backward frames and the reference buffer is cleared every 20 frames. The results clearly show improvement in sharpness and motion smoothness. However, we acknowledge that more intelligent algorithms could be developed to remove motion jitter and to indicate the static background so that more reference frames can be used to produce better results on such areas.

V. CONCLUSIONS

This paper has introduced a new method for mitigating atmospheric distortion in long-range surveillance imaging. Significant improvements in image quality are achieved using region-based fusion in the DT-CWT domain. This is combined with a new alignment method and cost function for frame selection to pre-process the distorted sequence. The process is completed with local contrast enhancement to remove haze interference. CLEAR offers class-leading performance for offline extraction of enhanced static imagery and has the potential of high performance for on-line mitigation for full motion video - this is the topic of ongoing research. Experiments with real data show superior performance compared with existing methods. Using simulated data, full reference metrics clearly show the superiority of this method. We have also introduced a new metric, QSVR, based on support vector regression for blindly assessing image quality. This learning-based method shows higher correlation with the FR methods than existing NR methods.

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