SUPPRESSION OF ATMOSPHERIC TURBULENCE IN VIDEO USING AN ADAPTIVE CONTROL GRID INTERPOLATION APPROACH

David H. Frakes, Joseph W. Monaco, Mark J. T. Smith

School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA

ABSTRACT

Atmospheric turbulence is a naturally occurring phenomenon that can severely limit the resolution of long distance optical and infrared sensors. Because atmospheric turbulence can degrade the appearance of video captured by these sensors, many of which are already deployed in the field, there is much interest in employing enhancement/restoration processing to improve data quality after acquisition.

This paper presents a signal processing approach to suppressing atmospheric turbulence effects in sensor video using an adaptive control grid interpolation method. In this method a dense dynamic motion vector field is derived from the characteristics of the atmospheric turbulence as seen in the data. The vector field is used in turn as part of the distortion compensation process, while preserving naturally occurring motion, such as that associated with the movement of objects within the stationary scene. The resulting algorithm is shown to produce enhanced video with quality significantly higher than that of the original.

1. INTRODUCTION

Atmospheric turbulence arises from a complex set of interrelated factors, such as wind velocity, temperature, elevation, sun intensity, and so on. For distant objects being viewed through a sensor, atmospheric turbulence can make those stationary objects appear blurred and the time-varying nature of this turbulence can make the objects appear to waver in a slow quasi-periodic fashion. Such a phenomenon is typically observed on a hot day at the airport looking out over the heated tarmac where the air hovering close to the ground appears to ripple with a wavy motion. The degradation we see arises from the refraction index fluctuations caused by the hot moving air, which perturb the incident wave fronts of the reflected light.

In theory, one can model the physical process underlying atmospheric turbulence and based on that model compensate for the distortion by way of Wiener filtering or other classical restoration methods. This observation has motivated several authors to propose restoration-based post processing algorithms for enhancement [1-5]. As with any model-based approach of this type, the quality of restoration will depend on the accuracy of the model. In cases where the turbulence model is an explicit function of parameters that describe atmospheric conditions, such as temperature, wind velocities, humidity, and sun illumination, restoration can be difficult to implement.

Rather than attempting to model turbulence as a function of atmospheric conditions, we take the approach of exploiting the property that the distortion effects are spatially local and temporally quasi-periodic. From this vantage point, the task is to estimate the spatially local displacement vectors dynamically and accurately and reconstruct distortion-compensated image frames with high quality. Toward this end we have developed an algorithm as described next, based on a modified form of control grid interpolation (CGI), which we employ to calculate vectors that describe pixel movement. This in turns forms the foundation upon which the turbulence suppression algorithm is built.

2. THE ALGORITHM

The first step of our procedure is to increase image resolution by a factor of four using bilinear interpolation, the purpose of which is to facilitate sub-pixel accuracy. Next we perform spatial filtering using an inverse Laplacian emphasis filter to enhance the high frequency information contained in the individual frames. After spatial filtering, control grid interpolation (CGI) is used to calculate vectors that describe the movement of pixels from one image to another. In the CGI representation as proposed by Sullivan [6], the motion field is obtained by segmenting the image into small contiguous square regions, the corners of which form control points. These control points are used as the anchors from which motion vectors in between are derived via bilinear interpolation. Unlike block matching which is employed pervasively in conventional motion compensated prediction for estimating motion vectors, CGI is attractive for this application because it allows for the representation of complex non-translational motion. In this work, however, we employ a high resolution CGI algorithm with embedded optical flow equations for calculating the motion of the CGI control points. This enables us to achieve an accurate dense motion field representation. Figure 1 shows an example of the motion field for a turbulent frame obtained from the algorithm, where the vector magnitudes have been scaled by a factor of twenty for visualization purposes.

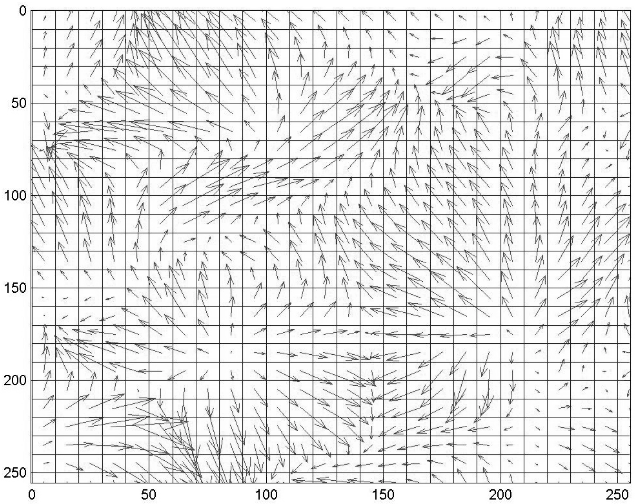


Figure 1. Magnitude enhanced motion vector field.

2.1. Bilinear Parameter Estimation

Within each block, the relationship between pixels in images $I_0[\mathbf{n}]$ and $I_1[\mathbf{n}]$ is described by Equation (1). In Equation (1) $d_1[\mathbf{n}]$ is the horizontal component of the displacement vector at spatial location (n_1, n_2) and $d_2[\mathbf{n}]$ is the vertical component. In each block, $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are computed with an iterative estimation strategy. This is equivalent to finding the optimal motion vectors at each of the control points at the border of the region.

$$I_1[\mathbf{n}] = I_0[n_1 + d_1[\mathbf{n}], n_2 + d_2[\mathbf{n}]]$$
$$d_1[\mathbf{n}] = \alpha_1 + \alpha_2 n_1 + \alpha_2 n_2 + \alpha_3 n_1 n_2 = \boldsymbol{\alpha}^T \boldsymbol{\theta}[\mathbf{n}]$$
$$d_2[\mathbf{n}] = \beta_1 + \beta_2 n_1 + \beta_2 n_2 + \beta_3 n_1 n = \boldsymbol{\beta}^T \boldsymbol{\theta}[\mathbf{n}]$$

Equation 1

The bilinear parameters are found in each region R by minimizing Equation (2).

$$\sum_{\mathbf{n}\in R} \left(I_0[\mathbf{n}] - I_1[n_1 + \boldsymbol{\alpha}^T \boldsymbol{\theta}[\mathbf{n}], n_2 + \boldsymbol{\beta}^T \boldsymbol{\theta}[n]] \right)^2$$

Equation 2

Using a first-order Taylor series approximation where all higher order terms are discarded, the error function in Equation (2) can be approximated by Equation (3). As long as a solution exists, Equation (3) can be solved with a matrix inverse to yield the desired model parameters.

$$\sum_{\mathbf{n}\in R} \left(I_0[\mathbf{n}] - I_1[\mathbf{n}] - \frac{\partial I_1[\mathbf{n}]}{\partial n_1} \boldsymbol{\alpha}^T \boldsymbol{\theta}[\mathbf{n}] - \frac{\partial I_1[\mathbf{n}]}{\partial n_2} \boldsymbol{\beta}^T \boldsymbol{\theta}[n] \right)^2$$

Equation 3

The accuracy of the estimates computed with Equation (3) can be further increased by changing the location of the Taylor series approximation from (n_1, n_2) to $\left(n_1 + \boldsymbol{\alpha}^T \boldsymbol{\theta}[\mathbf{n}], n_2 + \boldsymbol{\beta}^T \boldsymbol{\theta}[n]\right)$ and updating the parameter estimates. This process usually converges in fewer than five iterations.

2.2. Segmentation

A quadtree is used to segment the image into rectangular regions. Each of these regions uses a fixed set of eight parameters to describe the bilinear motion field in the region. The quadtree is built as part of the motion estimation procedure as follows. At the beginning of the parameter estimation procedure the image is partitioned into equally sized $N \times M$ blocks and a one-leaf quadtree is created for each of these blocks. An initial set of eight motion parameters is estimated for each leaf. A single leaf from one of the quadtrees is split into four new leaves on each pass of the estimation procedure using a greedy strategy. The greedy strategy selects the split that yields the largest reduction in Equation (2) on each pass through the algorithm. Although the quadtree provides a mechanism to exploit the efficiency of large uniform motion, this situation is not encountered often. For the turbulence cases we have examined, the quadtree virtually always splits to its finest grain resolution.

2.3. Turbulence Compensation

The motion vector fields provide a measure for correction from one frame to the next. Individually, they do not provide the information to return displaced pixels to their true location, since all frames in the sequence are apt to be undergoing turbulence. However, collectively the motion fields can be used to estimate true displacement location. Since atmospheric turbulence is quasi-periodic, the turbulent motion vectors should sum to zero over a periodic cycle. Thus, we can use the sum of the turbulent motion fields over an estimated period to obtain a base frame for compensation. That is, once this frame has been determined, the vector fields mapping all of the turbulent frames back to the base frame can be used to correct for motion in the distorted images. The result of this correction is a video sequence in which atmospheric turbulence has been suppressed significantly. The video at this point is then filtered temporally to smooth intensity discontinuities that may have been induced by the turbulence, after which each frame is decimated back to its original size.

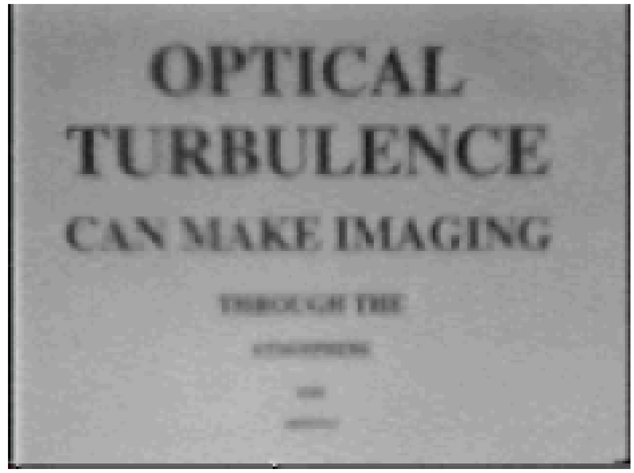
In the case where real motion is present in the video stream, an additional step is taken prior to motion correction. This step separates genuine motion vectors from turbulent ones. Genuine motion vectors are large in comparison to those induced by atmospheric turbulence, so they can be identified by thresholding. In both techniques we employed to perform this detection, the first step is to calculate the vectors mapping frame number n to frame number n+1. Although these fields will be mapping turbulent frames to other turbulent frames the discrepancy between genuine and turbulent motion vectors is substantial enough that the turbulent contribution to genuine motion vectors does not keep real motion from being identified.

Once n to n+1 mappings are calculated for the entire sequence, the first separation technique finds the median of all vector component magnitudes from a single frame's motion field, and compares that value to each of the vector component magnitudes associated with an individual pixel. Those vectors with component magnitudes exceeding the median by a certain percentage are classified as genuine motion vectors. The advantage of this technique is that it is time independent. After motion vectors have been calculated only one frame at a time is required to perform the separation. The second technique finds the median of the motion vector component magnitudes for a given pixel location in frames n, n-1, n-2, etc., and compares that value to the component magnitudes of the vector in the given pixel location of the current frame. Once again if either of that vector's component magnitudes exceeds a certain threshold then that motion vector is classified as genuine. The advantage of this technique is that it involves far fewer values in each median calculation while remaining causal.

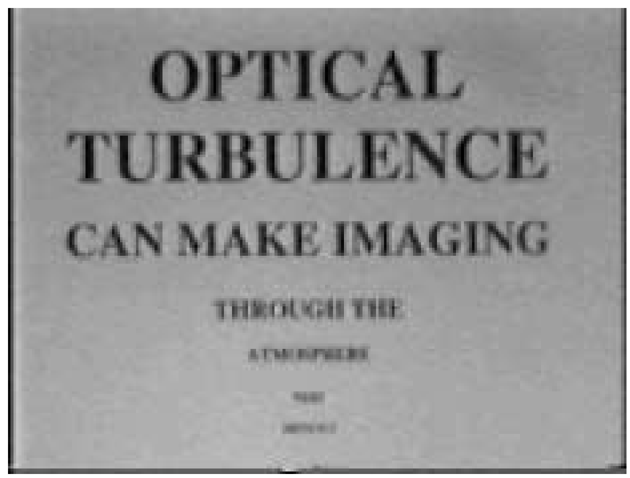
In both cases when a vector is classified as genuine, a flag in a matrix with dimensions equal to those of the image is set. This flag prevents the pixel from which the genuine motion vector originates from being altered by the motion correction algorithm that follows. It also keeps that pixel from being used in or altered by temporal filtering. The end result of the algorithm in the case that real motion is present is that the majority of the image has been corrected for degradation due to atmospheric turbulence but objects exhibiting genuine motion have been preserved.

3. RESULTS

Several video sequences provided by Gurton Army Research Lab in which atmospheric turbulence was present were processed with the algorithm. The results varied slightly with differing types of scenes, but the algorithm was effective in all cases. An example of an individual frame from an enhanced series is pictured in Figure 2 next to an individual frame from an original turbulent series.



Original



Enhanced

Figure 2. Single frames from original turbulent and enhanced sequences.

In a second example shown in Figure 3, we attempt to illustrate the improvement for a video sequence. One should keep in mind that the original is a video sequence in which the truck appears to waver over time creating a blurred effect. In an attempt to capture this video distortion in a single image for display purposes, we took the average of frames over one second. The blurring that is seen in the original is caused by the motion artifacts from atmospheric turbulence found in the frames of that sequence. The time averaging does expose turbulence in this fashion, but interestingly it also alleviates some of the turbulent effects present in the single frames of the original sequence because of the inherent quasi-periodicity. This fact is used to our advantage in the latter stages of the correction algorithm when temporal median filtering is employed. The genuine motion vector detection and isolation algorithm displayed successful results. This process was able to preserve real motion while correcting for the distortion due to atmospheric turbulence.

Original

Enhanced

Figure 3. Time averaged original turbulent and enhanced sequences.

4. CONCLUSIONS

The application of control grid interpolation to the correction of motion artifacts in video due to atmospheric turbulence proved effective on a variety of image sequences displaying stationary scenes. Unlike conventional motion estimation, the control grid interpolation method can provide a dense motion field while avoiding excessive computational complexity. Development of the technique allowed its application to video displaying both real and turbulent motion. Future work will continue the effort to make the algorithm more robust by enabling it to more accurately account for zooming and panning motion in video sequences containing atmospheric turbulence.

5. REFERENCES

[1] M. C. Roggemann and B. Welsh, *Imaging Through Turbulence*, CRC Press, Inc., 1996.

[2] D. Sadot, G. Lorman, R. Lapardon and N.S. Kopeika, "Restoration of Thermal Images Distorted by the Atmosphere, using Predicted Atmospheric Modulation Transfer Function", Infrared Physics and Technology, Vol 36, No. 2, pp. 565-576, 1995.

[3] M. C. Roggemann and J. A. Meindhart, "Image Reconstruction by means of Wave-Front Sensor Measurements in Closed-Loop Adaptive-Optics Systems," *J. Opt. Soc. Am. A*, Vol 10, pp. 1996-2007, 1993.

[4] P. Nisenson and R. Barakat, "Partial Atmospheric Correction with Adaptive Optics," *J. Opt. Soc. Am. A*, Vol 4, pp. 2249-2253, 1987.

[5] R. A. Muller and A. Buffington, "Real-time Correction of Atmospheric Turbulence Degraded Telescope Images through Image Sharpening," *J. Opt. Soc. Am. A*, Vol 64, pp. 1200-1210, 1974.

[6] G. J. Sullivan and R. L. Baker, "Motion compensation for video compression using control grid interpolation," in *Proceedings ICASP*, pp. 2713-2716, 1991.

[7] A. M. Tekalp, *Digital Video Processing*, Prentice Hall, Englewood Cliffs, NJ 1995.

[8] I. Sezan and R. Lagendijk, *Motion Analysis and Image Sequence Processing*, Kluwer Academic Publishers, January 1993.

[9] P.A. Sarginson, "MPEG-2: A Tutorial Introduction to the System Layer", Electronics Division Colloquialism. IEE, January 1995.

[10] Video coding standards world wide web resources:
http://www.iso.ch/welcome.html
gopher://gopher.itu.ch
http://www.cs.tu-berlin.de/phade(FAQ of MPEG)

[11] Joseph W. Monaco and Mark J. T. Smith, "Low Bit Rate Video Coding Using an Adaptive Partially Connected Motion Model," *Proceedings of the SPIE Visual Communications and Image Processing Conference*, February 1997.