The effects of gray scale quantization and saturation on MFBD and bispectrum SSA image reconstructions

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Abstract

The bispectrum and multi-frame blind deconvolution (MFBD) algorithms were developed to overcome the effects of turbulence and measurement noise in astronomical and space situational awareness systems. However, two non-ideal, but highly practical aspects of the measurements are not explicitly handled in the derivation of either of these algorithms: gray scale quantization, and the possibility of saturation. Minimizing the number of gray levels recorded allows the amount of data which must be recorded, stored, and processed to be minimized. However, gray scale quantization reduces the quality of the image reconstructions. Additionally, part of an image may occasionally saturate, causing a non-linear effect in the measurement, and also resulting in artifacts in the image reconstructions. We have investigated both of these issues, and report the results in this paper. Here we show that the effects of gray scale quantization are smaller for the MFBD technique than for the bispectrum technique. We have also modified an implementation of the MFBD algorithm to account for saturation, and present the results.

Gray Scale Quantization Effects

- Question: What is the smallest number of bits of gray scale quantization *N* that will yield an acceptable reconstruction from turbulence-corrupted images using the bispectrum and MFBD algorithms.
- Here we address this issue using simulated data.
- Simulation used is a standard, and widely used technique for modeling isoplanatic imaging through turbulence.
- Input parameters:
 - $D/r_0 = 13.3$
 - $-\lambda = 1 \ \mu m$
 - mean rate of photo-electron generation = 2×10^8 per image
 - Camera modeled: Hamamatsu C9100-13 (see the Hamamatsu web site: <u>http://sales.hamamatsu.com/en/products/system-division/cameras/all-uv-vis-ir-cameras.php?#form</u>), well depth = 370,000 electrons.

Bispectrum and MFBD Algorithms

• Gray scale quantization model:

$$G(x, y) = \text{floor}\left[\frac{K(x, y)}{\Delta e}\right]$$

$$K(x, y) = \text{photo} - \text{electrons at image location}(x, y)$$

$$\Delta e = \text{number of photo} - \text{electrons per gray scale level} = \frac{\text{well depth}}{2^{N}}$$

- Bispectrum algorithm used here is a MATLAB, vectorized implementation of a widely used bispectrum technique.
- MFBD algorithm is a fully parameterized, joint object/aberration estimation algorithm, run for 500 iterations [Billings, 2001].

16 bit bispectrum



x(object space), m

16 bit MFBD



14 bit MFBD



12 bit bispectrum

bispectrum estimated image





-5 0 5 x(object space), m

12 bit MFBD



10 bit MFBD mfbd estimated image

20 40 60 80 100 120

8 bit bispectrum

bispectrum estimated image





80 100 120



mfbd estimated image



6 bit MFBD mfbd estimated image



20 40 60 80 100





- <u>Conclusions</u>:
 - MFBD and bispectrum reconstructions suffer from different artifacts due to finite gray scale quantization.
 - As few as 6 bits of quantization yield acceptable reconstructions for the cases examined here.
 - It appears reasonable to reduce the number of bits used to quantize the data to as few as 8 bits to improve the speed of data transmission.

Saturation Effects on MFBD

- Real scenes cause pixels to saturate occasionally, e.g., glints from highly reflective parts of otherwise dim satellites.
- Saturation is a non-linear effect, and can not be modeled using the linear systems approach to describing MFBD.
- Our approach to slightly modify the model for the noise free images, and propagate the consequences of this change through the analysis and code.

Standard Model:

PSF estimates = $\{h_k(x_I)\}$ object estimate = $o(x_I)$ noise free images = $\{g_k(x_I)\}$, $g_k(x_I) = h_k(x_I) * o(x_I)$ Modified Model:

 $\hat{g}_{k}(x_{I}) = v_{k}(x_{I})g_{k}(x_{I}) + c_{k}(x_{I})$ $v_{k}(x_{I}) = \text{valid pixel mask} = \begin{cases} 1 & \text{for "good" pixel} \\ 0 & \text{for saturated or stuck pixel} \end{cases}$ $c_{k}(x_{I}) = [1 - v_{k}(x_{I})] \times [\text{saturation or stuck pixel value}]$

Simulations

- The simulation was used to make a data set with saturated pixels present by increasing the mean number of photo-events per image.
- $D/r_0 = 13.4$, Nyquist sampled, shot noise-limited data, 100 frames, with 128×128 pixels.
- Four cases of saturation were run:
 - Case 1: avg # of saturated pixels = 6.94 per frame (0.04%)
 - Case 2: avg # of saturated pixels = 124.89 per frame (0.76%)
 - Case 3: avg # of saturated pixels = 354.54 per frame (2.2%)
 - Case 4: avg # of saturated pixels = 2025.45 per frame (12.36%)
- OCNR5 satellite model used as the object.
- 200 MFBD iterations run, for each case.

Average Images for the Four Cases

20 40 60 80 100 120

20 40 60 80 100 120

object estimate obtained with saturation information

object estimate obtained ignoring saturation

object estimate obtained with saturation information

Conclusion

- Gray scale quantization adversely affects both bispectrum and MFBD reconstructions.
 - It appears that 6 bit quantization is sufficient to yield good reconstructions.
- Incorporating information about saturation into the forward model and gradient calculations for MFBD improves the quality of the reconstructions.