Image Enhancement for Astronomical Scenes

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ABSTRACT

Telescope images of astronomical objects and man-made satellites are frequently characterized by high dynamic range and low SNR. We consider the problem of how to enhance these images, with the aim of making them visually useful rather than radiometrically accurate. Standard contrast and histogram adjustment tends to strongly amplify noise in dark regions of the image. Sophisticated techniques have been developed to address this problem in the context of natural scenes. However, these techniques often misbehave when confronted with low-SNR scenes that are also mostly empty space. We compare two classes of algorithms: contrast-limited adaptive histogram equalization, which achieves spatial localization via a tiling of the image, and gradient-domain techniques, which perform localized contrast adjustment by non-linearly remapping the gradient of the image in a content-dependent manner. We extend these to include a priori knowledge of SNR and the processing (e.g. deconvolution) that was applied in the preparation of the image. The methods will be illustrated with images of satellites from a ground-based telescope.

1. INTRODUCTION

Ground based telescope images of astronomical objects are generally destined for either computational or visual analysis. The latter process is hindered by the fact that many such images have a high dynamic range (HDR). This makes many image features virtually impossible to display via low dynamic range media such as printed pages and computer monitors. To maximize the visual quality of the image, the dynamic range must be compressed. Uniform contrast and histogram adjustment techniques will do this, but the artifacts left behind by some processing techniques can be overly emphasized by some compression schemes. More recent work in the gradient domain has shown exceptional results for high SNR images [2], compressing the dynamic range without the halo effects typically present. However its performance on images with a very low SNR is unknown. In this paper we examine the effectiveness of gradient domain methods on noisy images with low SNR as well as comparing Contrast Limited Adaptive Histogram Equalization (CLAHE) methods to these Gradient Domain High Dynamic Range Compression (GDHDRC) algorithms, and to a simple unsharp mask of the log image.

2. DESCRIPTION

The three compression schemes used here are described in sections 2.1-2.3. Section 2.4 details the scoring method used to determine the quality of the HDR compressed image.

2.1 Contrast-Limited Adaptive Histogram Equalization

CLAHE methods separate the image into a number of tiles, and then adjust the contrast such that the tile histogram has the desired shape. The tiles are then stitched together using bilinear interpolation [1]. The specific implementation used here is that found in the 2012b version of Matlab, in the function 'adapthisteq'. In order to optimize the algorithm for a specific image, the number of tiles, number of histogram bins, and clipping level are adjusted. The histogram distribution can also be varied between Poisson, exponential, and uniform. Increasing the number of tiles decreases the size of each individual tile and the size of the features that are present in each tile.

Thus increasing the number of tiles allows the compression to better differentiate small features from the background, while making large features less uniform, as they consist of many independently normalized small tiles. The number of histogram bins affects the smoothness of the image, setting the number of gray levels that can be used. The clipping level "clips" the distribution at the user defined limit, helping adjust contrast.

2.2 Gradient-Domain High Dynamic Range Compression

The GDHDRC algorithm applied here is based on the paper by the same name [2]. The technique applies a nonlinear mapping to the gradient of the image, so that large gradients are attenuated more strongly than small gradients. The intention of this is to reduce the contrast change between adjacent sharply-defined areas of light and darkness while preserving visible detail in both the light and dark areas. The image is then reconstituted from the modified by solving a Poisson equation. The gradient attenuation is determined by two variables, referred to in the work by Fattal et. al. as α and β. The former variable determines which gradient magnitudes are attenuated, and the latter variable determines the degree of attenuation. To normalize the behavior of the process as a function of spatial frequency, the gradient of the (log) image is evaluated at each level of a Gaussian pyramid. The number of pyramid levels can be adjusted to reduce the low frequency components present in the recombined image, thereby emphasizing the smaller features of the image. In some cases adjusting the pyramid levels improves the quality of the HDR compressed image, but it is a far less pronounced change than one achieves by modifying variables α and β.

2.3 Unsharp Mask of log Image

UMLI is a homomorphic filtering [3] technique that involves subtracting a blurred copy of the log image from the log image. The effect of subtracting the blur is to remove large-scale brightness variations in the image, leaving local contrast unimpaired. A multiplicative factor is applied to the unblurred log image, i.e.

$$\textit{Corrected Image} = \exp\left(\mu \log(I) - \log(I) * G \right) \quad (1)$$

Where G is a Gaussian function with a known, user defined width (σ), and μ is a user defined constant. The corrected image is optimized by varying the values of μ and σ. The variable σ has an effect similar to the number of tiles in the CLAHE code, and the Gaussian pyramid level in the GDHDR code, where adjusting it changes the feature size that the compression is sensitive to. Increasing σ reduces the frequency threshold of the information being removed from the corrected image, this serves to sharpen the image much the same as a traditional unsharp mask, while working in tandem with the effect of μ to reduce the dynamic range.

2.4 Scoring Visual Improvement

In order to quantify the effectiveness of each method, the Visual Information Fidelity (VIF) [4] metric was computed. VIF measures the visual quality of the image by calculating the mutual information between a reference scene and a processed scene in a perceptually relevant wavelet basis. Unfortunately, since VIF requires a pristine reference image, it is not possible to use it to score processed field data. Instead, we used renderings of CAD models of satellites as our reference images. These include bright areas (sun-illuminated shiny metal) as well as deep shadows. Simulated telescope data were generated by convolving the pristine images with two ensembles of simulated point spread functions (PSFs) to represent very good and very poor seeing conditions (i.e. weak and strong turbulence). The degraded images were then processed with a multi-frame blind deconvolution (MFBD) algorithm to produce scenes representative of typical reconstructed images. A third dataset was generated by adding Gaussian noise to the pristine image convolving with a Gaussian kernel. The result is an approximation of an unreconstructed satellite imaged from a ground based telescope. All three test images (reconstructed with poor seeing, reconstructed with good seeing, and blurred) have a dynamic range large enough that very few details are visible without post-processing. A pristine image with dynamic range such that all features are visible is used as the reference for computing the VIF score. The test images were processed by each HDR compression algorithm and the variables adjusted until the VIF score was maximized. This was considered to be the optimal image for that algorithm.

3. RESULTS

3.1 Natural Scenes

The performance of gradient domain methods on high SNR scenes is very good. Figure 1 compares the three different compression schemes optimized by eye on the image used by Fattal et. al. to illustrate their GDHDRC algorithm. As expected, the GDHDR processed image is visually pleasing. The other enhancement schemes are less effective. Some features are too dark to make out (note the building directory on the wall) and others too bright to distinguish (the courtyard seen through the window in the CLAHE image).

The low SNR case in Figure 2 is more interesting to those working with astronomical scenes. To produce the source image, noise and blur were added to the scene from Figure 1. The GDHDR image is still a great improvement over the original, however the increased acutance in the UMLI is much more noticeable in this case, and serves to improve the visual appearance of the result. The CLAHE image has enhanced the contrast in the noise as well as in the image features, making it more difficult to distinguish between the two. This comparison illustrates that the optimal HDR compression scheme for high SNR images is not necessarily the best for the low SNR case.

Figure 1. High SNR scene compressed with (clockwise from upper left): no processing, gradient domain high dynamic range compression, contrast limited adaptive histogram equalization, and the unsharp mask of the log image.

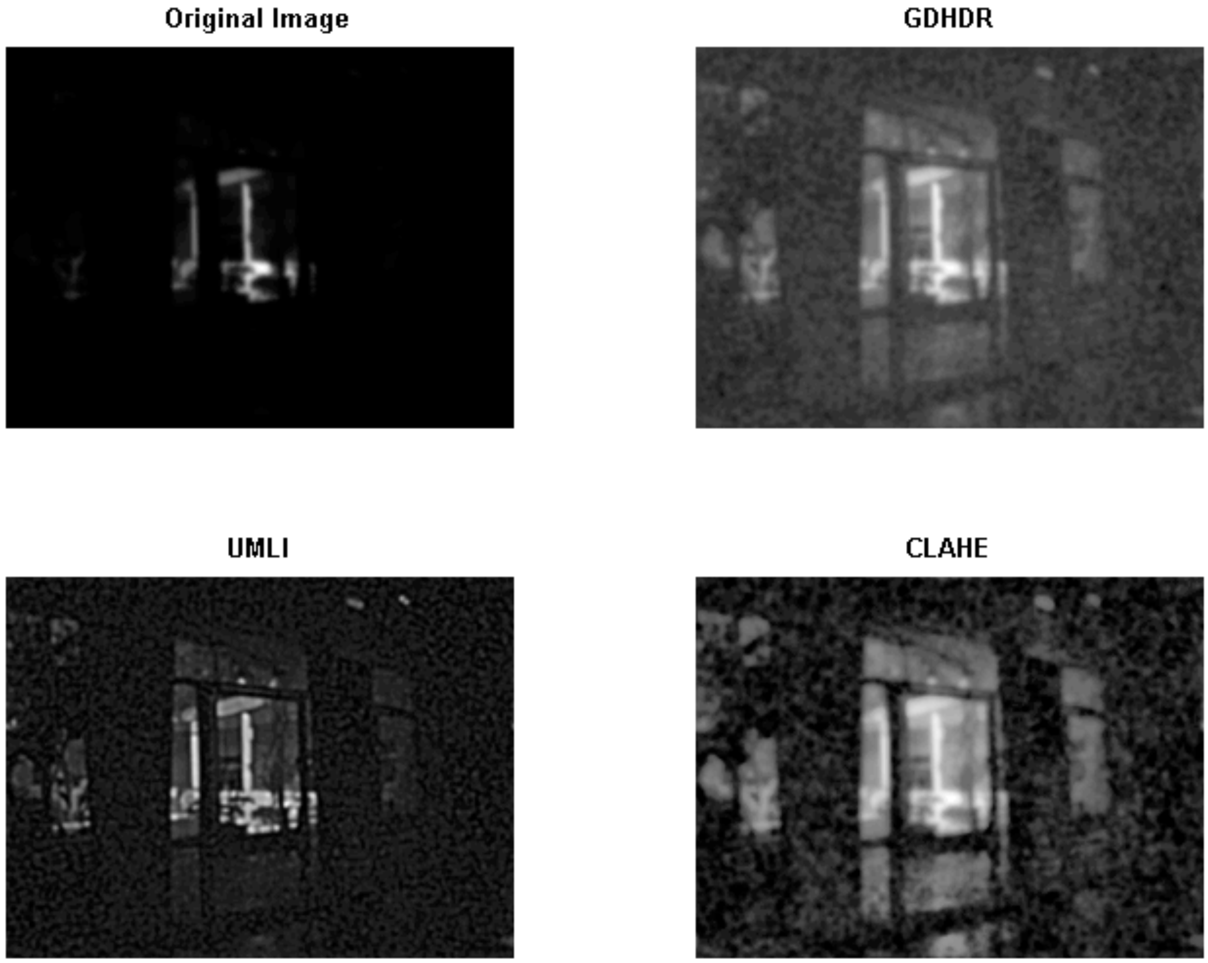

Figure 2. Low SNR scene compressed with (clockwise from upper left): no processing, gradient domain high dynamic range compression, contrast limited adaptive histogram equalization, and the unsharp mask of the log image.

3.2 VIF Scored Images

The three HDR images described in section 2.4 were HDR compressed with each method and the result scored with VIF. The results are summarized in Table 1 and displayed in figures 3-5. Figure 3 displays the compressed image representing good seeing. All of the images are a large improvement over the original, however the GDHDR and CLAHE methods display some artifacts not present in the UMLI compression. In the GDHDR processed image there is a noticeable blur around all features with a black background, this blur is introduced by the MFBD reconstruction; however the GDHDR code makes it more visible than either UMLI or CLAHE codes. The CLAHE compressed image has irregular blotches that are a result of the tiles being stitched back together. This effect can be minimized by reducing the number of tiles, but doing this reduces the contrast between small features such as the antennae towards the center of the image. None of the compressions are perfect, however the UMLI compression is appears superior, and this is supported by the VIF score.

Figure 4 shows the performance of these techniques with an image representing bad seeing. The GDHDR image still displays the halo present in Figure 3; however it succeeds in suppressing much of the halo visible in the UMLI image. This is at the expense of the visibility of small features such as antennae, which are more visible in the UMLI and CLAHE images. The CLAHE image retains the blotchy appearance seen in Figure 3, but using a large number of tiles means that it can reduce the majority of the halo without reducing the contrast on the small features.

Table 1. VIF scores for each compression method for the three scored image. Highlighted cells represent the best visual image as scored by VIF.

	VIF Score			
	GDHDR	**UMLI**	**CLAHE**	**Unprocessed Image**
Simulated Reconstruction With Good Seeing	0.435	0.488	0.422	0.12
Simulated Reconstruction With Bad Seeing	0.197	0.188	0.203	0.073
Simulated Un-Reconstructed Image	0.086	0.095	0.088	0.037

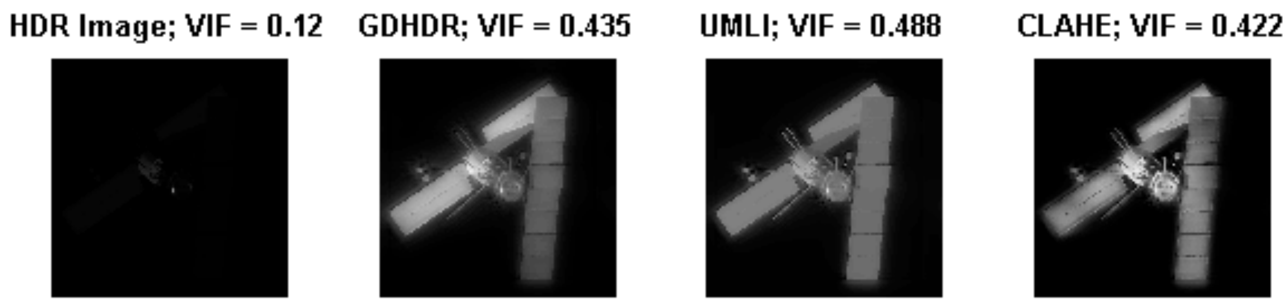

Figure 3. Reconstructed image representing good seeing conditions compressed with (from left to right): no compression, gradient domain high dynamic range compression, unsharp mask of the log image, and contrast limited adaptive histogram equalization.

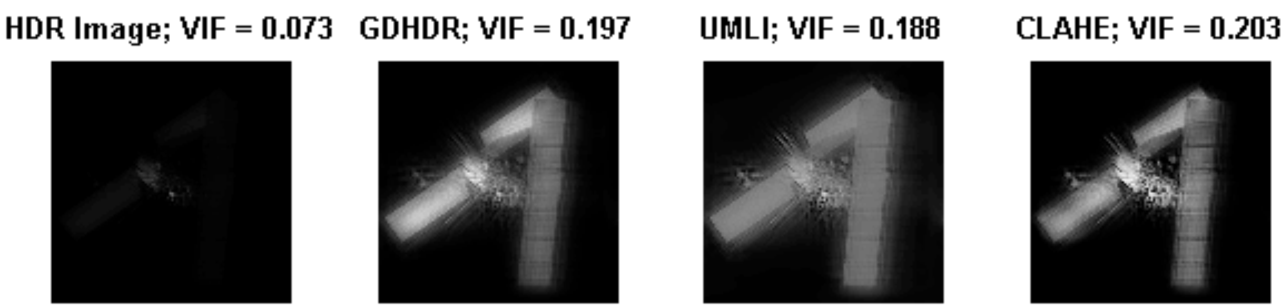

Figure 4. Reconstructed image representing poor seeing conditions HDR compressed with (from left to right): no compression, gradient domain high dynamic range compression, unsharp mask of the log image, and contrast limited adaptive histogram equalization.

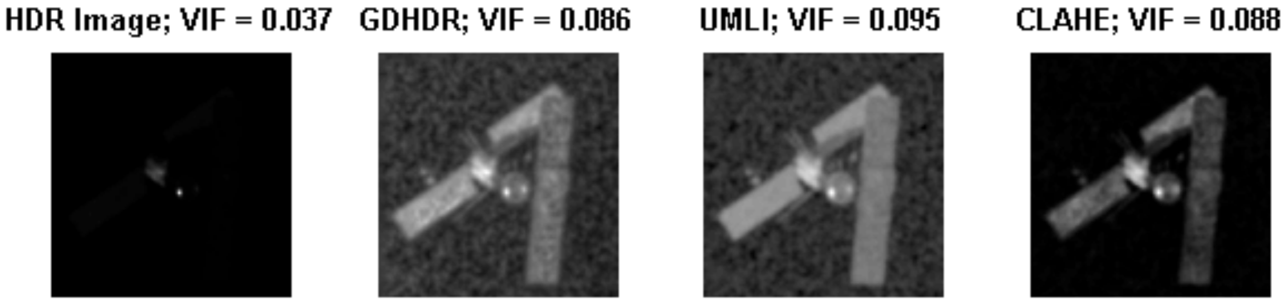

Figure 5. Image representing poor seeing conditions HDR compressed with (from left to right): no compression, gradient domain high dynamic range compression, unsharp mask of the log image, and contrast limited adaptive histogram equalization.

The images in Figure 5 are compressions of an image representing an unreconstructed image from a ground based telescope. The GDHDR image has emphasized the background much more than both the UMLI and the CLAHE methods. The GDHDR and CLAHE compressions both retain the noise in the object, where the UMLI compression has minimized this. Although the object is quite visible in all compressions, in the UMLI image the object is much smoother.

3.3 Ground Based Telescope Images

The difference compression schemes were applied to actual ground based telescope images. The image in Figure 6 is an MFBD reconstructed image, the image in Figure 7 is an AO compensated image that has not been reconstructed.

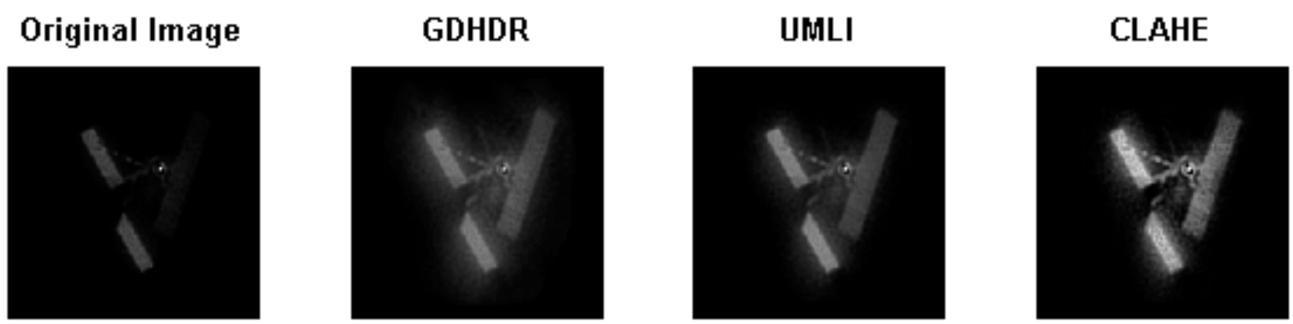

Figure 6. Reconstructed image HDR compressed with (from left to right): no compression, GDHDR, UMLI, and CLAHE methods.

Figure 6 continues the trend seen in figures 3-5. The UMLI image is the smoothest image, with less noise in the object itself, while bringing out some of the halo. The CLAHE compression has some non-uniformity but brings the object out from the background well with little halo. In contrast the GDHDR image brings out the halo quite strongly In Figure 7 the object in the CLAHE image is brighter, while in the UMLI image it is displayed with greater acutance. The GDHDR image displays the object, but with a distinct blur present.

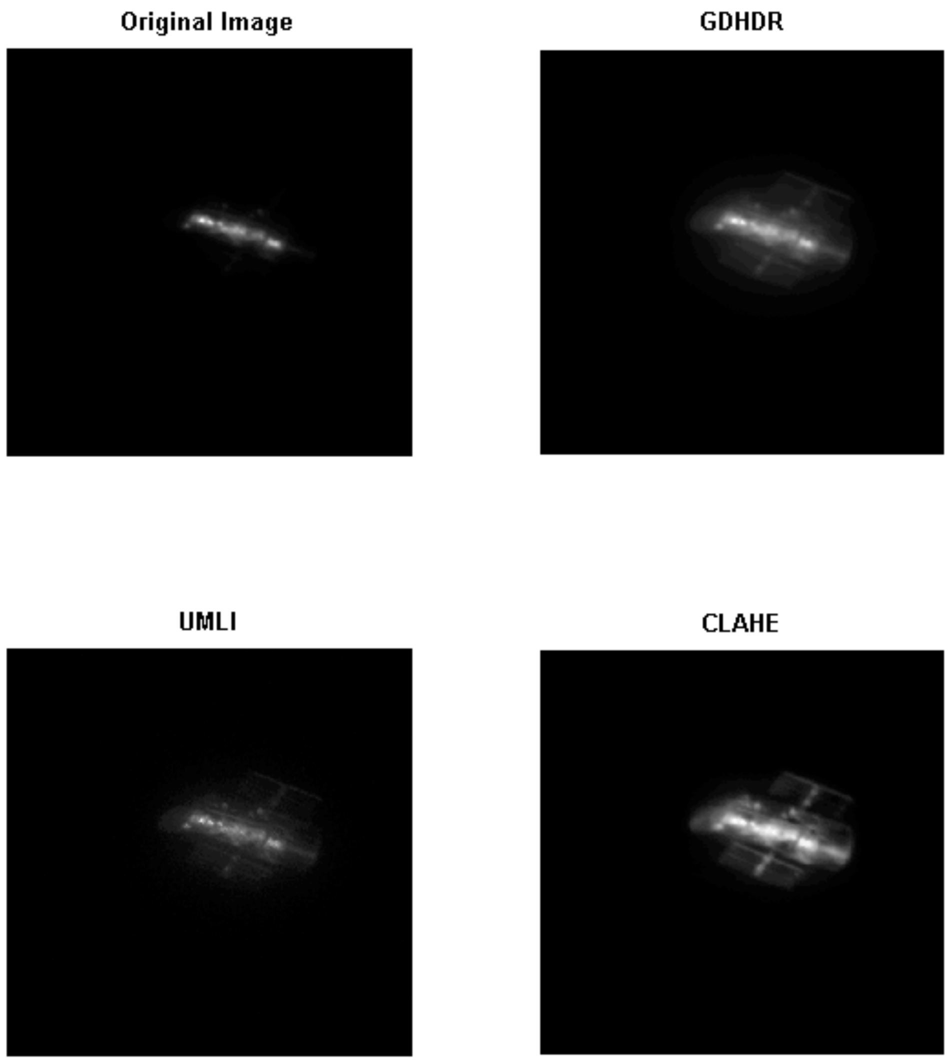

Figure 7. AO compensated image HDR compressed with (clockwise from upper left): no processing, gradient domain high dynamic range compression, contrast limited adaptive histogram equalization, and the unsharp mask of the log image.

4. CONCLUSIONS

By qualitatively viewing the images, as well as examining the VIF scores for the three scored images, of the approaches examined here the most consistent compression method for use with astronomical scenes appears to be UMLI. It is clear that there is no single solution for all images, as illustrated by the comparison in section 3.1. The criteria that make an algorithm work well for natural scenes can and do inhibit performance when compressing sparse images with a low SNR. Astronomical scenes, which are typically blurry and containing artifacts, require a compression scheme that can reduce the dynamic range in a manner that accentuates the object while actively reducing any halo or artifacts. Compressing natural scenes requires that all features be emphasized, as there is little noise or blur to take into account. The low SNR nature of astronomical scenes means that a global approach to dynamic range compression will always have difficulty making very dim object features (i.e. the central antenna in Figure 6) visible without also making visible the surrounding noise. While the methods detailed here all improve the visual quality of the image, a “smart” algorithm that can distinguish between the object and the surrounding noise and preferentially adjust the contrast is the ideal solution.

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