A review of bit depth expansion using minimum risk classification and adaptive interpolation

Amy Cheng
Department of Biomedical Engineering
Duke University
Durham, North Carolina
Email: abcheng15@gmail.com

***Abstract---* Bitmap images often use 8, 10, or 12 bits to represent each color channel of a pixel. When content created or compressed at a lower bit depth is displayed on a screen with higher pixel resolution, visible banded artifacts are produced. This effect is apparent in streaming commercial media that has been compressed for higher bitrates. There is a commercial need for fast bit depth expansion methods that remove the false contours without blurring edges or introducing excess noise. Major challenges include time and space complexity of computation and the subjective nature of the result. In this paper, I review some extant methods of bit depth expansion, including zero padding, ideal gain, a minimum risk-based Bayesian classification, and introduce a method using novel adaptive Laplacian interpolation.**

Keywords--- Bit depth, Laplacian interpolation, posterization, color quantization, adaptive filter, grayscale resolution, minimum risk, Bayesian classifier

I. INTRODUCTION

The advances made in displays and screens have made it possible to represent image and video with very high spatial, temporal, and pixel resolution. Most digital images are represented using raster graphics as matrix-like data structures (bitmaps). Each pixel in that data structure has 3 associated color channels for red (R), green (G), and blue (B). Conventional monitors use 8 bits to represent the value for each color channel, spanning values from 0 to 255. Modern screens are capable of displaying each color channel with more than the typical 8 bits, often going up to 10 or 12 bits. This increase in pixel resolution, or "bit depth," may seem like an obvious improvement over 8-bit representation. However, because (1) content created before the era of high bit depth monitors is made for 8-bit displays, and (2) streaming services often compress data to reduce the bitrate, the use of a high bit-depth display can have unintended consequences. Notably this comes in the form of posterization artifacts, sometimes called banding. This creates false edges in the image where there should be smooth gradients. The display of low bit-depth content on a high bit-depth machine will lead to these disturbing visual artifacts. In this paper, I review several known methods of expanding bit depth to minimize these artifacts, as well as introduce a novel method using adaptive Laplacian interpolation (ALI).

II. METHODS

A. Zero padding and multiplication by an ideal gain

Some of the most typical ways to expand an image of bit depth L to a higher bit depth H are zero padding (ZP) and multiplication by an ideal gain (MIG). In zero padding, H-L bits of value 0 are added to the least significant end of the pixel value. This is equivalent to multiplying the pixel value by the fixed value 2^{H-L}. Similarly, MIG multiplies each pixel value by a constant gain G described in (1).

$$G = \frac{2^H - 1}{2^L - 1} \tag{1}$$

The advantage of these methods is the ease of computation – they are virtually real-time. However, the result of both ZP and MIG lead to contouring artifacts, as shown in Fig. 1.

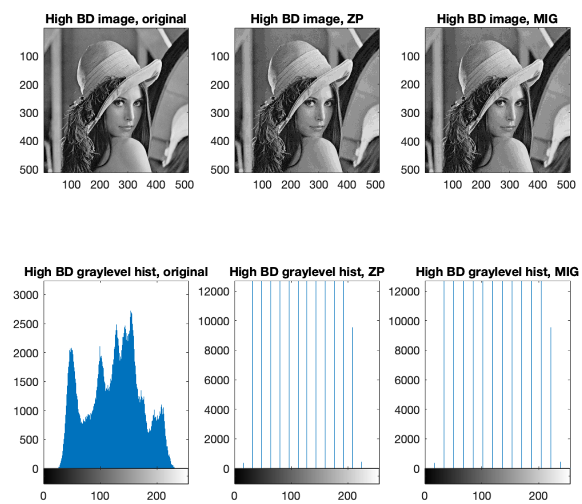

Figure 1: (top left) The 8-bit original Lena image. (top middle) A 4-bit version of the Lena image expanded to 8-bit using ZP. (top right) A 4-bit version of the Lena image expanded to 8-bit using MIG. (bottom) The associated gray level histograms for each image in the top panel, with values ranging from 0 to 255.

The regions where false contours appear the most prominently seem to be smooth gradients spanning large areas. For example, the shoulder in the Lena image appears striated when expanded with ZP or MIG.

B. Minimum risk-based classification

Mittal et al. coined a minimum risk-based Bayesian classification method in 2012 [1], which we will refer to as MRC. A Bayesian estimator is a decision rule that minimizes the posterior expected loss. This technique iterates through each pixel of the MIG image and finds the potential value of that pixel with the least Bayesian risk involved. This is heavy in computation, as it not only iterates through every pixel of the image, it also performs 2^{H-L} independent calculations for each pixel. The algorithm is as follows:

1. Generate the MIG image.
2. Blur the MIG image using an averaging filter.
3. Create a normalized error distribution function (EDF) of the difference between the MIG image and the averaged image (Fig. 2). This will serve as the posterior probability.
4. For each of the 2^{H-L} values possible for a pixel, calculate conditional risk using the EDF and the quadratic cost function (3).
5. Choose the value with the least associated risk and assign it to the pixel in the final image.

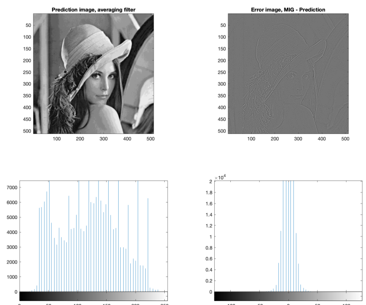

Figure 2: (left) Average-filtered MIG image and histogram. (right) The error image produced from the difference of the MIG image and the average-filtered MIG image, with its (pre-normalized) histogram.

Equation (2) describes the formula in step 4, which is a sum of posterior probabilities weighted by the cost function λ. This is the conditional risk of classifying a pixel into category i given an observation x. The cost function used is the quadratic cost function, as described in (3). The closer a category is to the "true" category, the less risk, and vice versa. This function measures the variance of the estimate.

$$R(i|x) = \sum_{j=1}^{2^4} P(j|x)\lambda(i|j) \tag{2}$$

$$\lambda(i|j) = (i-j)^2 \tag{3}$$

C. Adaptive Laplacian interpolation

In crafting a simple solution to the problem of false contouring in bit depth expansion (BDE), I considered the proposed method. Fig 3. shows one row of the Lena MIG image, with the grayscale value or local variance as the y-axis on the bottom graph. The local variance is a calculated using a "sliding window," similar to a moving average.

As mentioned above, the false contours generated from BDE using MIG are most noticeable in areas of the image that are smooth, large gradients. In the Lena image, her shoulder is an obvious example. In the original 8-bit image, the shoulder is a smooth gradient, lightening progressively left-to-right. However, in the MIG image expanded from 4 bits, the shoulder gray levels are still increasing, but in discrete jumps resembling step functions. These sharp transitions are a clear cause of the banding effect seen in the image. The regional variance is intuitively lowest in those flat, "blocky" areas, as confirmed by the bottom panel of Fig. 3. In sharp edge areas like the skin-hair transition, the variance is high.

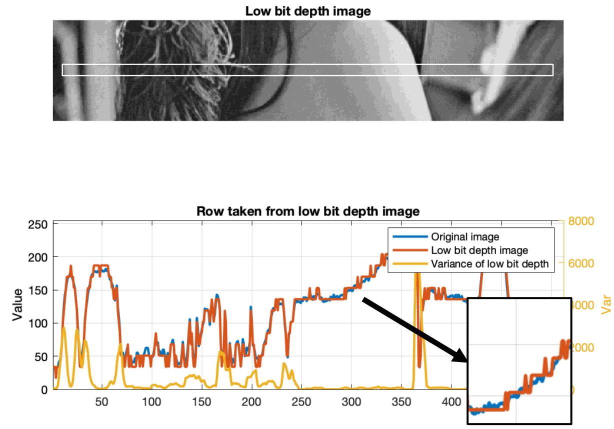

Figure 3: (top panel) A selection of the low bit-depth Lena image, with the region of interest bounded by a white box. (bottom panel) The values associated with the original 8-bit Lena image, the 4-bit image, and the local variance of the 4-bit image. A zoomed in portion of the shoulder is provided for clarity.

After concluding that these regions high in banding are also low in variance, a natural progression is to examine the regional variance in both dimensions (displayed in Fig. 4). This is calculated with a two-dimensional moving window and reveals the edges in the image, both natural and artificial. However, the natural edges have a much higher variance (indicated by the white) than the artificial edges (gray).

Figure 4: The local variance of the 4-bit Lena image, calculated with a window size of k=5.

After calculating the local variance, I compare it to the global variance of the image. Regions where the local variance is greater than the global variance are considered natural edges and are left untouched in the product. Regions where the local variance is less than the global variance are considered areas needing smoothing. This is similar to the adaptive mean filter, which weighs the importance of a pixel based on the ratio of global and local variance. A binary mask is created from the comparison of local and global variance, as shown in Fig. 5. The areas in white are the smooth regions, while the areas in black are the edges.

Figure 5: A binary mask used to segment smooth regions from edge regions. Calculated by comparing the local variance to the global variance.

After segmenting the image into areas to be smoothed and areas to preserve, there remains the question of how to smooth the banded regions. In my proposed method, I used interpolation. The black regions in Fig. 5 are used to interpolate the white regions, filling the region with information only from the black pixels. The interpolation used is Laplacian interpolation, which is ideal for filling in missing pixels given known locations and values of "seeds" (in this case, the black pixels of Fig. 5.) Each unknown pixel (white) has an associated equation, making the interpolation a sparse linear system that can be solved using the biconjugate gradient method. A preliminary result of this method is shown in Fig. 6. Closer examination reveals that there are still distinct bands in the smooth regions, but they are much smoother than before. Further results are provided in the Results section. This method is similar to a previously proposed contour region reconstruction method [2] but is innovative in its method of segmentation.

Figure 6: The initial result of interpolating the smooth regions defined by the mask by pixels outside of those regions.

III. RESULTS

In comparing the results of bit depth expansion using MIG, minimum risk classification, and adaptive Laplacian interpolation, I considered the subjective results as well as the peak-to-peak signal to noise ratio (PSNR), mean squared error (MSE), and structural similarity index (SSIM). All examples discussed in this paper use bit depth expansion from 4 bits to 8 bits, and compare results to the original 8 bit image before truncation.

Fig. 7 shows the difference in each image after processing with MIG, MRC, and ALI. The histograms associated with each image indicate that MIG results in the most discrete gray levels, with no values in between the 16 bins. The histogram of the MRC image is less discretized, with more intermediary values. It resembles the histogram of the original image more than the MIG does. The histogram of the ALI image, like the other methods, still has a majority of pixels in the bins present in the MIG histogram. However, there are many more intermediate values represented, and the histogram appears to resemble the original image's most of the three methods.

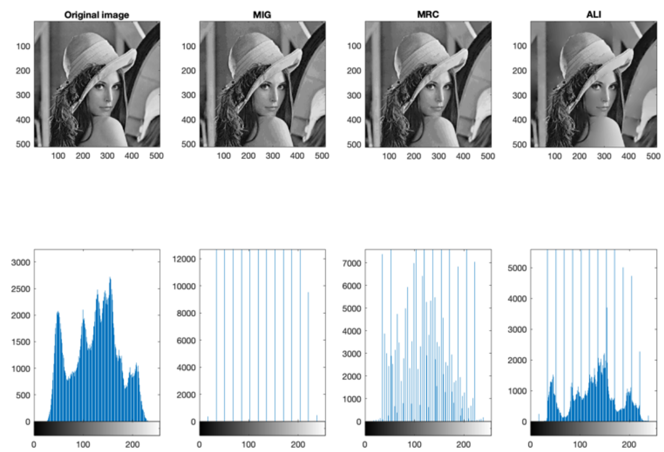

Figure 7: Comparison of the original high bit-depth image with the three methods reviewed in this paper, as well as each image's associated gray level histogram. (Left to right) The original image, the MIG method, the MRC method, and the ALI method.

Fig. 8 provides a zoomed in view of a portion of the Lena image. As stated previously, the contouring artifacts produced by bit depth expansion are most prominent in areas of smooth gradients, such as the shoulder in the Lena image. Examining this region, it is clear that the MIG and MRC results are similar, with perhaps slightly smoother transitions in the MRC image. However, the visible difference is negligible. The ALI image is smoother, and its contours are less visible. However, it is worth noting that the hair-skin edge on the left portion of the image in Fig. 8 has developed a slight halo in the ALI image. This is likely due to the imperfect segmentation of regions in the ALI method.

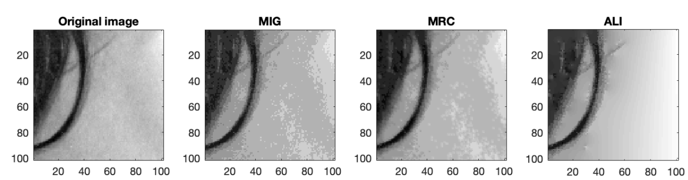

Figure 8: Zoomed-in selections of the results in Fig. 7. (Left to right) The original image, the MIG method, the MRC method, and the ALI method.

I also evaluated bit depth expansion on the cameraman image in Fig. 9. Vertical contour artifacts are prominent in the sky behind the man in MIG and MRC. The ALI image does not appear to have these artifacts looking at the full image, but zooming in reveals some subtle banding. The high detail areas of the image (e.g. the camera) seem to be largely preserved by all methods. Looking at the edge between the man's hair and the sky, it appears that MIG and ALI introduce white halos.

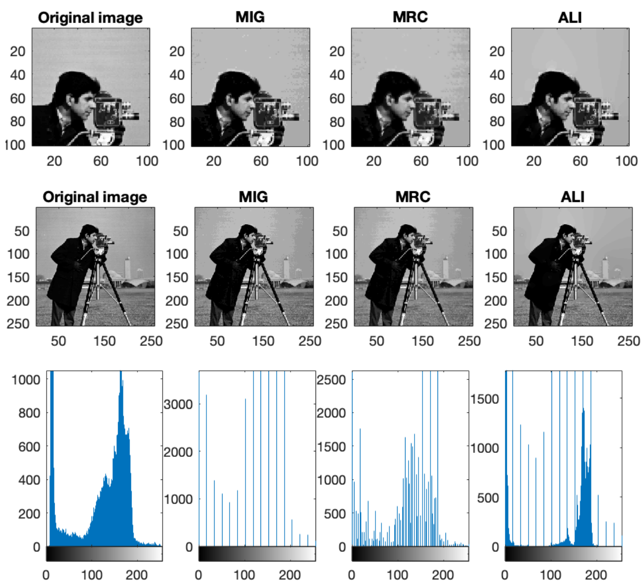

Figure 8: The results of bit depth expansion on the cameraman image. The top panel provides a zoomed in portion of the middle panel, while the bottom is the histograms of each image.

In addition to qualitative evaluation, I also assessed each technique by its PSNR, MSE, and SSIM. The results are presented in Table 1.

TABLE 1. PSNR, MSE, AND SSIM FOR BDE METHODS

1	**Performance metrics for Lena image**		
	PSNR	***MSE***	***SSIM***
MIG	32.8197	33.9715	0.8719
MRC	33.9426	26.231	0.9068
ALI	29.0891	80.2002	0.8877
2	**Performance metrics for cameraman image**		
	PSNR	***MSE***	***SSIM***
MIG	31.2709	48.5278	0.8165
MRC	31.7838	43.1221	0.8553
ALI	29.7110	69.4992	0.8686

IV. CONCLUSION

Of the methods discussed in addressing the visual artifacts produced by bit depth expansion, I suggest using my adaptive Laplacian interpolation technique. Bit depth expansion is an ill posed problem, and the optimal outcome is largely based upon visual assessment. Zero padding and MIG lead to visible artifacts that may impact consumer enjoyment of visual media. However, techniques similar to the Bayesian risk classifier are computationally expensive in both time and space, and the result may not be worth the effort of implementation. My method of adaptive Laplacian interpolation is both quick and effective, making false contour artifacts less noticeable while preserving important features in the image. However, this increase in visual clarity comes at the cost of increasing mean squared error, when compared to other methods. In addition, this method creates white halos on sharp edges. Despite these disadvantages, I believe the visual improvement of ALI-expanded images outweighs the decrease in signal and increase in noise. Given the methods described in the scope of this paper, I propose ALI as a simple, fast, and effective technique to mitigate the effects of bit depth expansion.

V. REFERENCES

[1] G. Mittal, V. Jakhetiya, S. Jaiswal, O. Au, A. Tiwari, and D. Wei, "Bit-depth expansion using Minimum Risk Based Classification," IEEE Visual Communications and Image Processing, 2012.

[2] C. Cheng, O. Au, C. Liu, and K. Yip, 'Bit-depth expansion by contour region reconstruction," in . of IEEE Int. Sym. on Circuits and Systems, May 2009