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Image Debanding Using Iterative Adaptive Sparse Filtering

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Abstract

Due to a limited bit-depth representation of pixel values and lossy compression methods, an image may exhibit annoying banding or false-contouring artifact. Existing banding-removal approaches mainly include low pass filtering, dithering and re-quantization. In this paper, we propose an image debanding method that iteratively improves the image using a content-adaptive spatial filter. The filter uses adaptive span based on local width of the band and operates on 1D sparse pixel-window. The input image is filtered in each direction i.e. vertical, horizontal and two diagonals sequentially while offering parallel processing in each direction. The iterative framework gradually improves the quality of filtered image until it converges to the final output. Experimental results show that our proposed method is effective in debanding images.

Introduction

Banding is a major visual artifact that exhibits in the form of visible "bands" in an image and such bands often change with time creating significant annoyance to viewers [1-3]. When such images are displayed as a video, banding becomes visually more annoying due to the "shifting" effect of bands/false contours in various regions of video. It causes poor subjective scores and mediocre viewing experience. Figure 1 shows an example of banding in the sky region.

FIGURE 1: BANDING ARTIFACT IN IMAGE: AN EXAMPLE

Banding can happen as a result of several factors [1]. During content-capture, the camera pipeline may not provide enough bit-depth to store sensor output. Post processing methods can reduce bit-depth of the image signal while storing/transmitting it to the next stage. Poor image compression often exacerbates the existing false-contouring artifacts. It becomes important to remove these bands or "deband" such images in a variety of image/video processing applications.

Many of image debanding approaches consist of the use of 1D/2D spatial filters. While others employ a more recent convolutional neural network (CNN)-type of methods. While it is a well-studied topic, challenges still remain due to the computational allowance for processing, latency and implementation-complexity constraints. A fixed-span low-pass filter may not be suitable for all content considering varying width of bands. Thus, it is important to design a content-adaptive filter. Multiple directions e.g. vertical, horizontal and diagonal need to be filtered to do image debanding. One filtering operation an image may not be enough to remove banding. Thus, we investigate multiple iterations of the multi-directional adaptive filter to improve the debanded image quality.

In this paper, we propose an iterative multiple-scan adaptive sparse filter for effective and efficient image debanding. Our main contributions are:

- A 1D adaptive sparse filter (ASF) in which parameters are tuned based on local signal properties is presented. Adaptive tuning of the filter-size according to the signal is quite effective in breaking down the steps (or bands).
- For debanding images i.e. 2D signals, a Multiple-scan ASF (MASF) is proposed. The key idea is to apply the 1D filter, sequentially along vertical (columns), horizontal (rows) and the two diagonals' direction, to the image pixels to achieve debanding in those directions.
- We also propose an iterative MASF (I-MASF) framework that employs MASF iteratively to an image until a stopping criterion is met. The main motivation is to successively deband the image until no further significant improvement is possible.

In the next section, we present an overview of existing image debanding approaches.

Related Work

In the past couple of decades, many approaches have been proposed for reducing or removing false contouring or banding artifact for a range of applications. Majority of the applications are consumer electronics such as television or other display devices [2-6]. There have been some efforts to reduce banding from medical imaging as well, mainly due to its impact on the detection and diagnosis [7].

Generally, banding detection and reduction using spatial filtering is the most popular approach. Adding noise/dither to reduce the visibility of bands, is another approach. Many methods use either one of these approaches or some combination of them. In [2], authors present a method for detecting and segmenting flat-region in the image to do bit-depth extension for removing false contours. A multi-scale method is proposed to first determine the presence and scale of banding using a likelihood score, followed by probabilistic dithering that reduces the visibility of banding [3]. A dithering-based method that uses Curved Markov-Gaussian noise, is proposed in [4]. However, the noise can often get annoying to viewers, especially when the level of noise is high. In another method, the dithering approach is employed to adjust each pixel value to break down the contouring bands, considering the gradient smoothness and block boundary smoothness with neighboring blocks [5]. Another approach consists of three steps [6]. The first step is to employ directional segmentation around a pixel and measure that how likely it has smooth area within the image. Then, an adaptive low pass filtering (LPF) is applied on the support region for its center pixel. Lastly, spatial dithering is applied to mask remaining banding. In [8], banding detection is done as a first step using a sign-based gradient approach. However, it reportedly fails in several cases of combinations of gradients. The iterative method used here to find filter size at each pixel is computationally costly. A frequency analysis is proposed to detect smooth areas followed by applying local filters [9]. A banding detection method for print systems is proposed in [10]. While it presents some very related ideas to banding detection on screen, the intent here is just to analyze the print quality of content. Another method categorizes an image into three parts: smooth area, "slow-change" area and texture area using classification methods [11]. Yet, it is restricted to just detection of the artifact, while not actually debanding the images. In [12], authors propose a false contour detection method that estimates the number of potential perceptually visible false contours in the decoded high dynamic range (HDR) image and iteratively adjusts the dynamic range compression parameters to prevent or reduce the number of false contours. Whereas in [13], a banding-alleviating inverse tone-mapping method is proposed. Here, the tone-curve is modified such that the resulting HDR image is banding-free. However, these methods are specific to HDR applications.

A pre-processing approach is re-quantization [14]. But this is useful only when we have the original signal. An edge-aware sparse filter is proposed for debanding inverse tone-mapped HDR images [15] as a hardware-efficient solution. While the sparse filter design is cost-efficient, it uses tone-curve information for determining the threshold of the filter, while other filter parameters such as filter span, are empirically set to fixed values. The fixed-span sparse filter from [15] has a drawback because a longer filter span is needed for effective smoothing of the wider bands, but it is not suited in case of narrower bands with non-monotonic trend.

Our proposed 1D filter determines the filter span adaptively based on the band properties computed based on pixel values to effectively smooth the 1D signal. Secondly, for debanding an image i.e. a 2D signal, directional 1D filters applied sequentially are useful. Vertical and horizontal filtering is not sufficient to remove bands at more angles. Thus, in addition to the two Cartesian directions, we propose using diagonal filtering for an improved performance. More angles can be possibly used to serially remove banding in other directions, but are computationally expensive. Thirdly, the filtered output image can still contain banding. Thus, we propose using an iterative framework to filter the output of the previous iteration to improve debanding performance, until a stopping criterion is met. Our proposed method is adaptive to image properties, effective in considerably reducing banding and parallel-processing friendly for efficient implementations.

Our Proposed Method

In this Section, we describe our proposed image debanding method. The proposed basic filtering unit is a 1D sparse filter that draws motivation from [15]. We present our content-dependent 1D ASF that consists of scanning bands to record signal properties and application of sparse filter with variable tap-distance. This 1D ASF is then applied to an image in various directions such as horizontal, vertical and diagonals to filter image-pixels. We call this filter as multi-scan ASF (MASF). For images with severe banding, an iterative MASF (I-MASF) is proposed to gradually reduce the banding.

1D Sparse Filter

We use the basic 5-tap 1D sparse filter proposed in [15]. As shown in Figure 2, the 1D sparse filter uses pixels placed at specific distances from the center pixel $s[\mathrm{k}]$, which is to-be filtered. More specifically, the locations of pixels to be used in filtering $s[\mathrm{k}]$ are $s[\mathrm{k} \pm q]$, $s[k \pm 2q]$, $s[k \pm (2q+e)]$. By design, $e = \left\lfloor \frac{(q-1)}{2} \right\rfloor$, where q is a parameter specifying the pixels involved in filtering the pixel $s[k]$ and $\lfloor . \rfloor$ is floor operation.

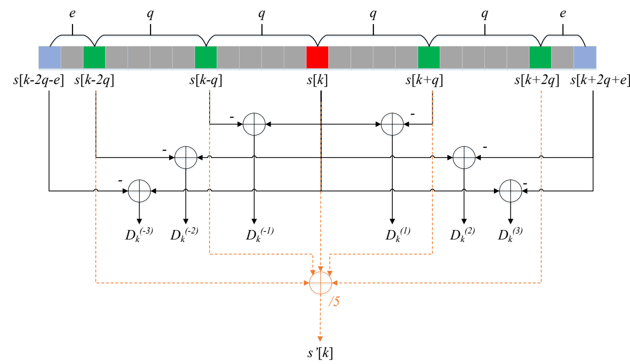

FIGURE 2: 1D SPARSE FILTER FOR SIGNAL SMOOTHING

We first compute the difference between pixel values of each non-center pixel with the center pixel $s[k]$. In total 6 such differences are computed for each of the 6 non-center pixels, we denote them as $D_k^{(i)}$, where $i = \{-3,-2,-1,1,2,3\}$ as shown in Figure 2.

The maximum absolute pixel difference $D_k^{(max)}$is:

$$D_k^{(max)} = \max\left(\left|D_k^{(i)}\right|\right), i = \{-3,-2,-1,1,2,3\}$$

If $D_k^{(max)} \leq Th$, we assign the central pixel, the average of 5 pixel-values: $s[\mathrm{k}], s[\mathrm{k} \pm q]$, $s[k \pm 2q]$. Let $s'[\mathrm{k}]$ be the filtered output. Therefore,

if $(D_k^{(max)} \leq Th)$

$$s'[k] = \frac{s[\mathrm{k}-2q] + s[\mathrm{k}-q] + s[\mathrm{k}] + s[\mathrm{k}+q] + s[k+2q]}{5}$$

else

$$s'[k] = s[k]$$

Evidently, this is a conditional sparse filter that uses Th, or threshold for filtering as a parameter controlling the debanding/smoothing performance.

If the above sparse filter is used with a fixed q (and resultingly, a fixed span of the filter) on entire image, the results are dependent on the selection of q. Regions of images with wide bands typically need a larger q to remove bands. If we increase q too much, parts of images tend to get over-smoothed which is also undesirable. On the other hand, a smaller q will result in less effective debanding capability. Consequently, tuning q adaptively based on local pixel parameters can significantly improve the picture quality. In our experiments to determine the optimal q, a test image with uniformly spaced "bands" with width W was used as input to the sparse filtering algorithm. We found that the smoothest output (uniform and small steps after filtering) is using

$q = m\left[\frac{W}{5}\right]$, where m is a positive integer constant and [.] is rounding operation. In other words, the distance between neighboring samples should be a multiple of $\left(\frac{W}{5}\right)$. The tunable parameter is W, which is tunable for each pixel and depends on the input 1D data.

Content-Adaptive Sparse Filter (ASF)

We propose adaptive distance (q) sparse filtering for effective debanding performance. Figure 3 shows the workflow of our proposed method using three steps.

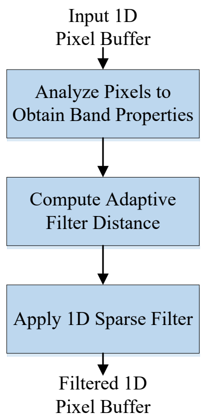

FIGURE 3: PROPOSED 1D ADAPTIVE SPARSE FILTER: A FLOWCHART

The input is 1D single channel (e.g. luma of YCbCr) pixel array (or buffer). Let P be the total number of luma pixels.

[A] Analyze Pixels to Obtain Band Properties: In the first scan along one dimension, each pixel value is compared to its neighbors to record band properties. We define "band" as a group of neighboring pixels having the same value. Assume we have N such groups, and each of which has a start and an end pixel index to indicate the location of the band, the pixel value (e.g. luma codeword) and the number of pixels or width W of the band. Let $\left(b_j^{start}, b_j^{end}\right)$ be the start and end pixel indices and α_j be the pixel value of all pixels belonging to the j'th band of the pixel buffer. The number of pixels in the j'th band $n_j = b_j^{end} - b_j^{start} + 1$.

Then, we refine the band properties to conditionally merge stray pixels to be a part of band. This also allows merging of two sizably wide neighboring bands but separated by just a small number of pixels whose values are very close but not the same as either of bands. Therefore, if all the following conditions are satisfied $n_{j+1} < n_{tol}$, $|\alpha_j - \alpha_{j+1}| \leq \alpha_{tol}$, $\alpha_j = \alpha_{j+2}$, we merge the j'th, $(j+1)$'th and $(j+2)$'th bands. We use $n_{tol} = 5$, $\alpha_{tol} = 1$ for 1080p original 10-bit SDR images on 48"~65". To apply this for 8-bit-to10 bit converted images, we should use $\alpha_{tol} = 2^{(10-8)} = 4$, to allow one 8-bit codeword tolerance. Figure 4 shows an illustration of this Step [A]. Bands 1, 2, and 3 are merged in this example.

[B] Compute Adaptive Filter Distance: In this step, we assign the required distance, q_j, for filtering each pixel in the j'th band. Based on our empirical analysis, we assign $q_j = m\left[\frac{n_j}{5}\right]$. Step [B] is illustrated in Figure 4, where q_j is assigned for each j'th band.

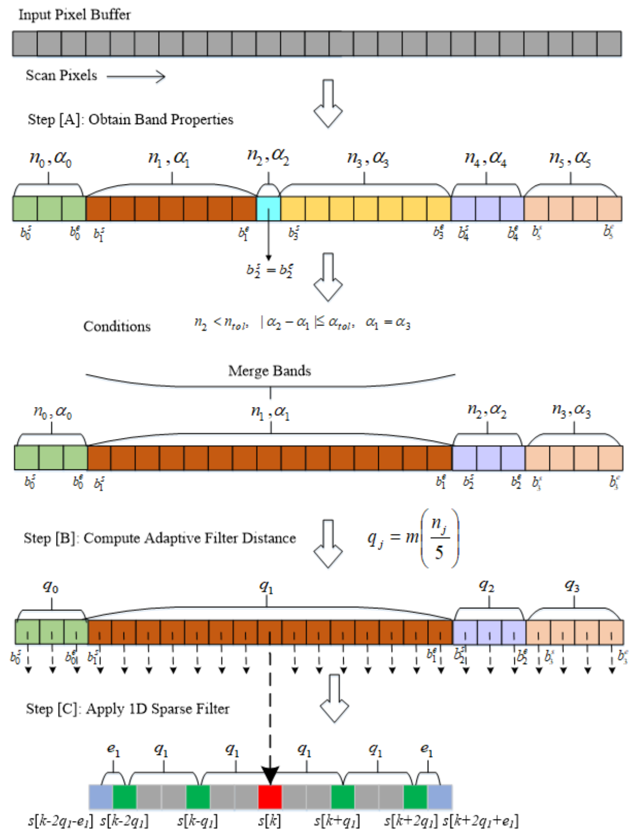

FIGURE 4: PROPOSED 1D ADAPTIVE SPARSE FILTER: AN ILLUSTRATION ($m = 1$)

[C] Apply 1D Sparse Filter: 1D sparse filter is applied on each pixel using its respective distance parameter q. Figure 4 shows an illustration of this as Step [C] applied to an example pixel.

Multi-Scan ASF (MASF)

It is observed that banding artifact in 2-D image can appear in different directions along different angles. To produce effective visual debanding outcome, we propose a multiple-scan approach in which we scan image vertically, taking each column of image, then horizontally (taking each row of image) and diagonally. The debanding operation in each direction will be done sequentially.

In each direction, we apply the 1D ASF separately on each column, row or diagonal-set of pixels. This also enables parallel processing to speed up the implementation. Figure 5 depicts MASF workflow.

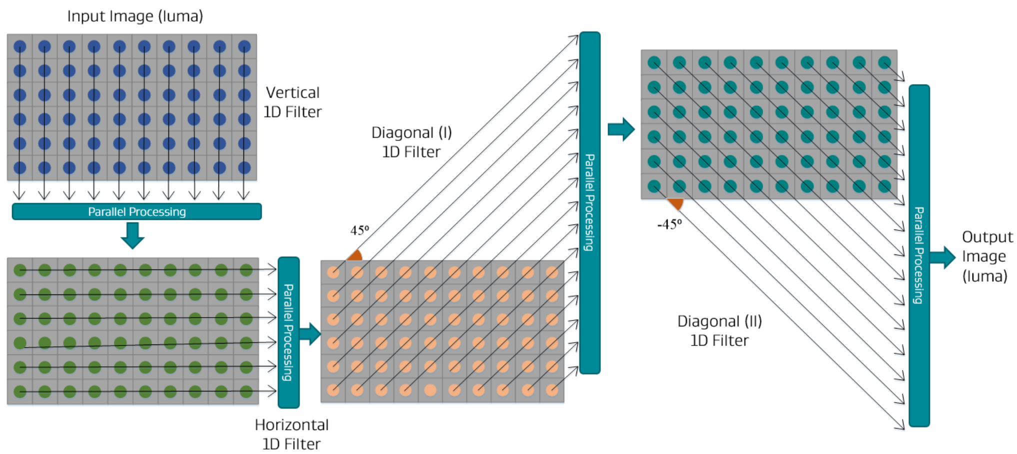

FIGURE 5: MULTI-SCAN ADAPTIVE SPARSE FILTERING FOR IMAGE DEBANDING (FLOW DIAGRAM)

Iterative MASF (I-MASF) Framework

In a few extreme cases, generally due to poor compression in the dark regions, there is still visible banding after one complete iteration of MASF algorithm. One way to address this is to increase the *Th* parameter of ASF. But it can remove necessary details such as texture/edges etc. Alternatively, if we run MASF on the output of the MASF, we see images getting smoother, reducing banding further. The key idea is that running MASF iteratively may help reduce banding in those extremely poor-quality images. Thus, we propose an iterative MASF algorithm (I-MASF) which runs MASF repetitively under some operating conditions.

The proposed I-MASF is shown in Figure 6.

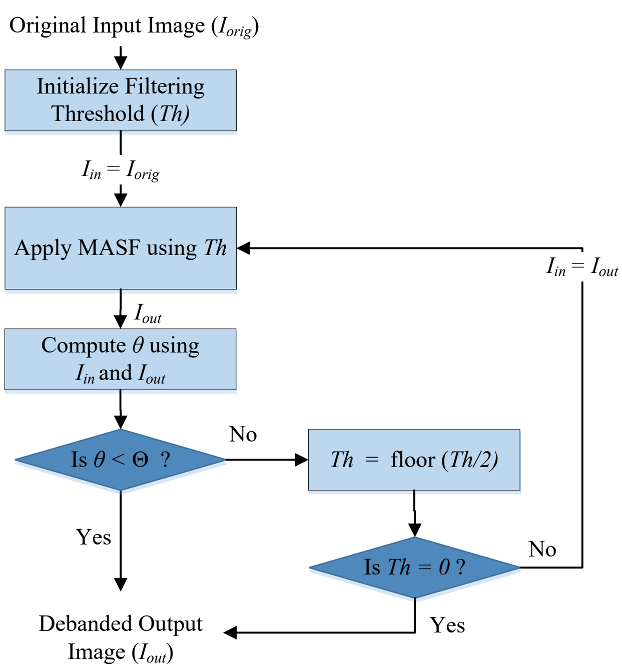

FIGURE 6: PROPOSED ITERATIVE MASF FLOWCHART

We begin the I-MASF with the input image I_{orig} (Y-channel). We then initialize input image $I_{in} = I_{orig}$ and *Th* to an initial value (say, *Th* = 16). After MASF, we get I_{out} as the output image of that iteration. Let *P* is total number of pixels in the image. Let $I_{in}(i)$ and $I_{out}(i)$ be the *i*'th luma pixel value of input and resulting image of MASF in the current iteration. Then, we compute θ, the average sum of absolute difference (SAD) per pixel between I_{in} and I_{out} of the current iteration.

$$\theta = \frac{1}{P}\sum_{\forall i} |I_{out}(i) - I_{in}(i)|$$

The average SAD helps determine whether the stopping criteria is satisfied or not. We reduce the threshold (*Th*) parameter by half and floor the value to integer.

Stopping criteria: the iterative process is terminated when either of the following two conditions is first met:

- $\theta < \Theta$: where Θ is a parameter stating the stopping average SAD per pixel, usually of a small value indicating a visually negligible change in pixel value.
- *Th = 0*: We stop the process because when *Th* = 0, it is equivalent to no pixel change after filtering.

Either (or both) of meeting the above stopping criteria indicates that no further processing will make image much better. Generally, Θ = 0.1/0.2 is reasonable based on our experiments.

If the stopping criteria is not satisfied, we apply another iteration of MASF filter on I_{out} from previous iteration (thus $I_{in} = I_{out}$) with the updated threshold *Th* to continue the iterative process.

Experimental Results

The proposed debanding method was implemented in C and tested using several single images and 230 short video clips. The images were coded using YUV 420 10-bit format and were of dimensions 720p, 1080p, 2160p, representing a wide range of content. Many of them contain banding in a variety of codeword range and of different severities. We used commercially available televisions to conduct subjective evaluation of our proposed image debanding method.

Figure 7 (a) shows an image from movie content. We observe the image contains banding in the highlight, mainly the bright sun region. Figure 7 (b) shows the result of our proposed debanding method. This image took only one instance of I-MASF to converge i.e. satisfy our stopping criterion. The resulting image shows banding-free image.

(a) Original Image

(b) Debanding Result (Proposed Method)

FIGURE 7: EXAMPLE I

A more illustrative example is shown in Figure 8. Here, the original image in Figure 8 (a) presents banding in the sky/sun region. Figure 8 (b) shows the result of first iteration of I-MASF where the luma SAD between the original and output image is 1.71/pixel. It can be observed that this image still contains visible banding and needs further processing for banding-free outcome. Since our stopping criterion is not satisfied with this SAD value, I-MASF continued with another iteration to further deband the image from Figure 8 (b). The result of second iteration is shown in Figure 8 (c) that produced the luma SAD 0.14/pixel. Since the stopping criterion (Θ = 0.2) is met, the image in Figure 8 (c) is declared as output which presented a visually pleasing image.

Whereas, Figure 9 (a) shows a user-generated content (UGC), captured with a mobile phone camera. It contains obviously banding in the sky region. The video containing this frame is more annoying since the bands shift in successive frames. Here, our proposed method applied two iterations of I-MASF before converging to the output image shown in Figure 9 (b). It can be observed that the result is free of banding and visually pleasing. Therefore, our proposed I-MASF method can produce debanded images that are visually more pleasing.

(a) Original Image

(b) Debanding Result: Iteration 1 (Avg. SAD = 1.71/pixel)

(c) Final Debanding Result: Iteration 2 (Avg. SAD = 0.14/pixel)

FIGURE 8: EXAMPLE II

Conclusion and Future Work

In this paper, we presented an iterative image debanding method that successively improves the image using a content-adaptive spatial filter. The input image is filtered in each direction i.e. vertical, horizontal and two diagonals. Multiple iterations of this directional filtering are employed to improve image quality. Experimental results show that our proposed method is effective in debanding images from a wide variety of content. In future, we plan to study more directions for applying 1D ASF on an image and also employ our method to chroma channels.

(a) Original Image

(b) Debanding Result (Proposed Method)

FIGURE 9: EXAMPLE III

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