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# Bound-Constrained Optimized Dynamic Range Compression

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Fig. 1. Our dynamic range compression method applied to different natural HDR images.

We present a new spatially-varying dynamic range compression algorithm for high dynamic range (HDR) images based on bound-constrained optimization using soft constraints. Rather than explicitly attenuating gradients as in previous work, we minimize an objective function to instead compute a globally optimal manipulation of input pixel differences. Our framework provides simple yet effective preservation of visually important image properties, such as order statistics and global consistency, that requires little to no parameter tuning. Our results are free of haloing, washout, and other artifacts, while retaining detail across the image's full range. The speed of our algorithm and flexibility of the constraint framework allows our method to be easily extended to video.

## 1 INTRODUCTION

Thanks to the ubiquity of high dynamic range (HDR) imaging, numerous dynamic range compression techniques have been developed over the years, in order to display this high dynamic range content on low dynamic range devices and software. These tone-mapping operators can be broadly grouped into two classes: global and local. Global operators work across the entire input image, mapping every input luminance to some output luminance according to a global adjustment curve at the cost of detail - many fine scale details are often washed out. In contrast, local operators use a mapping between input and output values that varies across the image, so that the output intensity of each pixel depends on its local neighborhood, resulting in strong detail preservation at the cost of spatial artifacting like haloing and ringing. In this work, we propose a new technique that uses an optimization framework to maximize the level of detail preservation, while ensuring that the results remain artifact-free.

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## 2 APPROACH

Dynamic range compression fundamentally seeks an image that maximally preserves the visual aspects of the input radiance map while using a smaller, specified dynamic range. If, like previous gradient-domain approaches, we quantify "visual aspects" in terms of pixel differences [Fattal et al. 2002; Mantiuk et al. 2006], we can write a penalty function $F(l_i - l_j, h_i - h_j, i, j)$ that represents the error for output log intensities $l_i$ and $l_j$ corresponding to input log intensities $h_i$ and $h_j$ at pixels $i$ and $j$. Armed with this function, we can now formulate dynamic range compression as a bound-constrained optimization problem:

$$\begin{aligned} \underset{l}{\text{minimize}} \quad & \sum_{i \in P} \sum_{j \in N_i} F(l_i - l_j, h_i - h_j, i, j) \\ \text{subject to} \quad & L_{min} \le l_i \le L_{max}, \; i = 1, \ldots, N \end{aligned} \tag{1}$$

where $P$ is the set of all pixels in the image and $N_i$ denotes the considered neighborhood of pixel $i$. In the ideal case, $N_i$ contains all pixels in $P \setminus \{i\}$, but for computational efficiency we use the immediate 4-connected neighborhood of $i$, as well as $s = 2$ other randomly selected pixels. The constraints bound the dynamic range of the output image $l$ to $[L_{min}, L_{max}]$. By using bound constraints, we ensure that the output of our algorithm optimally preserves detail and contrast for the desired dynamic range. As a result, our method does not explicitly attenuate pixel differences, as in existing gradient-domain methods [Fattal et al. 2002; Mantiuk et al. 2006]. Instead, the process of bound-constrained optimization determines the optimal attenuation according to the selected error function.

We further decompose $F(l_i - l_j, h_i - h_j, i, j)$ as the sum of a pixel difference preservation term $P(l_i - l_j, h_i - h_j)$ and an order statistic term $O(l_i - l_j, h_i - h_j)$, scaled by a weighting function $W(h_i - h_j, i, j)$:

$$\begin{aligned} & F(l_i - l_j, h_i - h_j, i, j) = \\ & \qquad W(h_i - h_j, i, j)\big(P(l_i - l_j, h_i - h_j) + O(l_i - l_j, h_i - h_j)\big) \end{aligned} \tag{2}$$

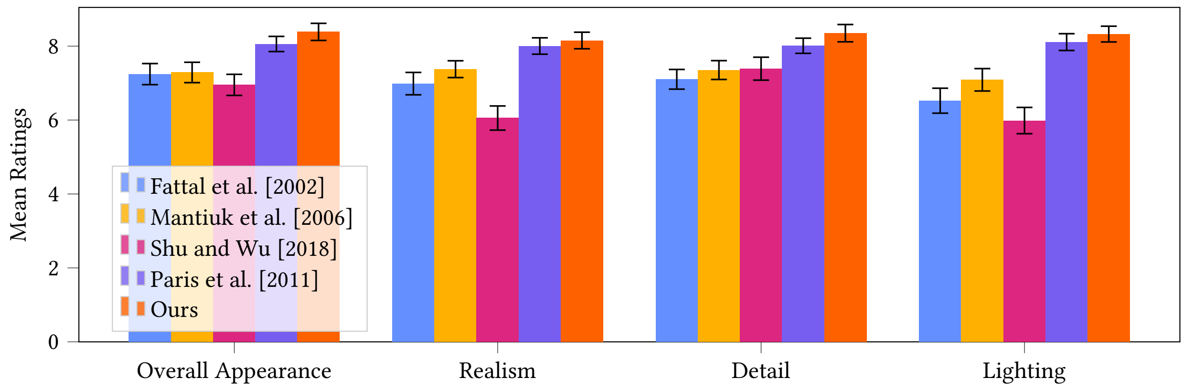



Fig. 2. Average ratings with 95% confidence intervals from our subjective study. Our method retains detail while preserving realism and correctness of lighting, resulting in the highest average scores in every category.

We describe our exact choices for these functions in further detail in the supplement.

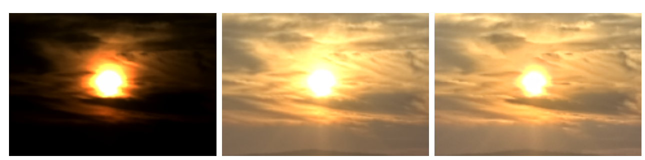
The combination of the weighting function $W(h_i - h_j, i, j)$ and the preservation function $P(l_i - l_j, h_i - h_j)$ control the level at which each input pixel difference is preserved in the output image. Pixel differences with a larger weight value given by $W(\cdot)$ will be more likely to be preserved by the optimization process, while pixel differences corresponding to smaller $W(\cdot)$ will most likely be compressed. The choice of $P(\cdot)$ is also equally important. For example, using a squared error term would encourage many variations from the input pixel differences to avoid one large variation. In contrast, using an absolute error term would concentrate the variations from the inputs in as few pixel differences as possible. In essence, like how gradient-domain operators manipulate the input image using an attenuation function, our approach allows for manipulation through careful design of the penalty function $F(\cdot)$. However, unlike previous gradient-domain operators, our approach never unnecessarily attenuates an input gradient, potentially increasing the level of detail preservation.

The order statistic term $O(l_i - l_j, h_i - h_j)$ penalizes changes in luminance ordering between the input and output images, important for preventing spatial artifacting [Shu and Wu 2018]. Global operators, thanks to their monotonic tone curve design, fundamentally preserve order statistics over the entire image. Therefore, if $N_i$ is the entire image $P$ and $O(\cdot) = \infty$ for violations of the order statistic, our optimization is a perfect global operator. In contrast, if $N_i$ is just the immediate neighborhood of pixel $i$ and $O(\cdot) = 0$ for violations of the order statistic, our optimization is a perfect local operator. Thus, the order statistic term $O(\cdot)$, combined with $N_i$, fundamentally provides a sliding knob between an ideal local operator and an ideal global operator.

## 3 RESULTS

In order to solve the optimization problem given in section 1, we rely on a hierarchical gradient descent solver with momentum. The hierarchical solver builds a Gaussian pyramid, solves the optimization for each level, and initializes the next level with the output of the previous one. To handle bound constraints, we simply clip invalid intensities to $[0, 1]$ at every iteration of gradient descent. With this setup, we achieve convergence within a hundred iterations at all but the coarsest level in every tested case. We implement our method using Python and Tensorflow, which can utilize GPU acceleration. We find that our method compares favorably to previous state-of-the-art operators [Fattal et al. 2002; Mantiuk et al. 2006; Paris et al. 2011; Shu and Wu 2018] in a user study in figure 2. We also show further results in the supplemental. Our method can also be easily extended to video, also described in the supplemental.

An important effect of our formulation is its improved handling of wash-out, as shown in figure 3. Our formulation explicitly uses the output dynamic range as part of the optimization process, removing the need for clipping. Simultaneously, thanks to its attenuate-as-needed approach, many of the high luminance details are not pointlessly reduced under our formulation.



(a) Clipped Input (b) Mantiuk et al. [2006] (c) Our method

Fig. 3. Without special care, many of the details in the clouds near the sun are lost after dynamic range compression.

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