Improved Image Selection for Stack-Based HDR Imaging

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Abstract

Stack-based high dynamic range (HDR) imaging is a technique for achieving a larger dynamic range in an image by combining several low dynamic range images acquired at different exposures. Minimizing the set of images to combine, while ensuring that the resulting HDR image fully captures the scene’s irradiance, is important to avoid long image acquisition and post-processing times. The problem of selecting the set of images that has received much attention. However, existing methods either are not fully automatic, can be slow, or can fail to fully capture more challenging scenes. In this paper, we propose a fully automatic method for solving an optimization problem that is either explicitly formulated as an integer linear program [10] or whose computational complexity is unknown but empirically known to be high [9, 12, 13].

In this paper, we propose a method for selecting the set of exposures to acquire that is both fast and more accurate, particularly on challenging scenes. Following previous work, our proposed method is also adaptive to the irradiance distribution and incorporates a model of camera noise. However, our method formulates the selection problem as a polynomially solvable set covering problem. We show on a total of 110 benchmark scenes that overall, in addition to being fast, our proposed method leads to improved HDR images over the state-of-the-art methods as measured against ground truth using the mean squared error, a visible difference predictor and a quality score, both perception-based metrics. Our experimental evaluation is also the first to extensively evaluate existing state-of-the-art methods for image selection for stack-based HDR imaging.

Background

In this section, we review some of the underlying concepts and routines used in methods for selecting the set of images.

Many cameras are able to record images in a proprietary RAW format in addition to the common JPEG format. The RAW images are linearly related to scene radiance [16, 17] and have a higher dynamic range (usually, 12–14 bits), while JPEG images are nonlinearly related to scene radiance and have a lower dynamic range (8 bits).

A camera radiometric response function $f$ is the nonlinear mapping that determines how radiance in the scene becomes pixel values in a JPEG image through the imaging pipeline of the camera. In our experiments, a response function was estimated using multiple pairs of RAW and JPEG images, all taken of the same scene but each pair taken with a different exposure. Alternatively, a response function can be roughly modeled using a standard gamma correction curve. Once the mapping is known, JPEG pixel values can be inverted back to an estimate of the RAW
In our experiments, we have also been proposed that estimate noise from a single image (see, e.g., [21]). The signal to noise ratio expressed in decibels is given by, \( \text{SNR} = 10 \log_{10}(\mu/\sigma) \), where \( \mu \) is the RAW pixel value and \( \sigma \) is the estimated noise at that RAW pixel value. SNR increases monotonically (up to sensor saturation) with increased exposure time and decreases monotonically with increased ISO gain. The SNR at saturation is zero by definition. Figure 2(b) shows example SNR(db) curves for a Canon EOS 5D Mark III camera. The empirical data can be fit with negligible residual error using the parametric noise model \( \sigma = \sqrt{\mu + c^2 + r^2} \), where \( g \) is the ISO gain, \( r \) is the read noise, and \( c \) is the noise component that does not depend on the signal or the gain (see, e.g., [10][18]). For the Canon EOS 5D Mark III camera, \( c \) is zero in the best fit.

The best methods for selecting the set of images rely on either being given an estimate of the extent of the dynamic range of a scene, or on being given an estimate of the full irradiance distribution in the form of an HDR histogram. In our experiments, we followed Healey and Kondepudy’s [18] procedure for estimating camera noise from multiple images, although methods have also been proposed that estimate noise from a single image (see, e.g., [21]). The signal to noise ratio expressed in decibels is given by, \( \text{SNR} = 10 \log_{10}(\mu/\sigma) \), where \( \mu \) is the RAW pixel value and \( \sigma \) is the estimated noise at that RAW pixel value. SNR increases monotonically (up to sensor saturation) with increased exposure time and decreases monotonically with increased ISO gain. The SNR at saturation is zero by definition. Figure 2(b) shows example SNR(db) curves for a Canon EOS 5D Mark III camera. The empirical data can be fit with negligible residual error using the parametric noise model \( \sigma = \sqrt{\mu + c^2 + r^2} \), where \( g \) is the ISO gain, \( r \) is the read noise, and \( c \) is the noise component that does not depend on the signal or the gain (see, e.g., [10][18]). For the Canon EOS 5D Mark III camera, \( c \) is zero in the best fit.

The key step is that we formulate the selection of the set of images for HDR imaging as a set covering problem.

**Definition 1** (Set covering). Let \( A = [a_{ij}] \) be an \( m \times n \) (0-1)-matrix with a cost \( w_j \) associated with each column. A row \( i \) of \( A \) is covered by a column \( j \) if \( a_{ij} \) is equal to one. The set covering problem is to find a subset of the columns \( C \subseteq \{1, \ldots, n\} \) that minimizes the total cost \( \sum_{j \in C} w_j \) such that every row is covered; i.e., for every \( i \in \{1, \ldots, m\} \) there exists a \( j \in C \) such that \( a_{ij} = 1 \).

Let \( \{t_1, \ldots, t_n\} \) be the ordered set of available shutter speeds on a camera. In the set covering instance, a row represents a pixel across the stack of low-resolution JPEG images (Step 1), a column represents a possible exposure setting \( t_i \) for that pixel, and an entry \( a_{ij} \) is 1 if and only if the pixel has been accurately captured by that exposure (Step 2). If the goal is to minimize the number of images selected, \( w_j = 1 \), and if the goal is to minimize the total capture time, \( w_j = t_j + \text{overhead} \), where \( \text{overhead} \) is the overhead between image acquisitions. In general, solving set covering is NP-complete [23]. However, here the set covering instance can be constructed to have the consecutive ones property, allowing the selection of images to be computed in polynomial time [24][25].

**Definition 2** (Consecutive ones property). A set covering problem is said to have the consecutive ones property if the ones in each row of the matrix \( A \) appear consecutively.
If all costs \( w_j \) are one, the following simple reduction rules alone solve an instance. Let \( M_i = \{ j : a_{ij} = 1 \} \) and \( N_i = \{ j : a_{ij} = 1 \} \), where \( i \in \{1, \ldots, m \} \) and \( j \in \{1, \ldots, n \} \).

R1. If \( N_i = \emptyset \), row \( i \) can be removed.
R2. If \( M_j \subseteq M_{j'} \) and \( w_{j'} = w_j \), column \( j \) can be removed.

If the costs are the shutter speeds, a polynomial algorithm can be used to find a solution after reduction.\(^{24,25}\)

Steps 4 & 5. As the final steps in our proposed method (see Figure 1), acquire high-resolution RAW images at the exposures specified by the solution to the set covering instance, and combine them into a single HDR image using existing techniques (e.g., \(^{26,27}\)).

In the form stated above, our proposed method chooses an exposure by setting the shutter speed, keeping the aperture and ISO gain fixed. Keeping the aperture fixed at the camera’s native ISO is desirable in stack-based imaging to reduce image noise and increase dynamic range (for the Canon EOS 5D Mark III camera, the native ISO is 100; see Figure 2(b) for the effect of ISO on image noise and dynamic range). However, increasing the ISO gain can be useful when the camera is not mounted on a tripod and a minimum shutter speed may be required to reduce the impact of camera shake, or to handle dynamic scenes \(^{8,10,13}\). Our proposed set covering method can seamlessly handle a fixed but higher ISO gain setting to ensure a minimum shutter speed: the low resolution stack will be acquired at the higher ISO (Step 1), the set covering will take into account the higher ISO when setting the interval \([I_{\min}, I_{\max}]\) for determining whether a pixel has been accurately captured (Step 2 & 3), and the high resolution images will also be acquired at the higher ISO (Step 4).

Experimental Evaluation

In this section, we experimentally evaluate the effectiveness of our proposed method for image selection.

We compare our proposed set covering method against four representative state-of-the-art methods: (i) Barakat et al. \(^{7}\), (ii) Hasinoff et al. \(^{10}\), (iii) Pourreza-Shahri and Kehtarnavaz \(^{15}\), and (iv) Seshadrinathan et al. \(^{13}\). All five methods rely to varying degrees, on knowing the camera response function, the noise level function, and the HDR histogram of the scene. The same routines were used across all methods (see “Background”). As well, when needed a threshold of 20 dB was used for determining whether a pixel has been accurately captured. The grayscale pixel value of 20 corresponds to an SNR of 20 dB for our Canon EOS 5D Mark III camera and the value of 230 was empirically determined to be the grayscale threshold where two or more component channels are rarely saturated. Pourreza-Shahri and Kehtarnavaz’s \(^{15}\) method requires the specification of a parameter \( w \), where \( w \) is used in clustering the dark and bright regions of the well-exposed image. We set \( w = 8 \), as in Pourreza-Shahri and Kehtarnavaz’s \(^{15}\) experiments. Similarly, Seshadrinathan et al.’s \(^{13}\) method requires the specification of \( N \), where \( N \) is an upper bound on how many exposures to consider. Because of efficiency considerations, Seshadrinathan et al.’s \(^{13}\) set \( N \) to be three in their experiments. In our experiments we set \( N \) to be five; larger values are impracticable.

We test the methods on the following benchmarks. In each benchmark, only the shutter speed was varied and the aperture and ISO gain were kept fixed.

- The HDR Photographic Survey \(^{29}\) suite consists of 105 benchmark image set. Each image set consists of nine images (with one exception) of a scene captured with a Nikon D2X camera. In each scene, the exposure step was set to one stop and a 4288 \( \times \) 2848 high resolution RAW image was acquired at each of the nine shutter speeds using the camera’s continuous auto-bracketing function. We converted each RAW image to JPEG using Nikon’s ViewNX software and downsampled to give a 960 \( \times \) 640 low resolution JPEG image that simulates the image that would have been acquired from the live preview stream at that shutter speed.
- We acquired five benchmark image sets using a camera remote control application we implemented. A Canon EOS 5D Mark III camera mounted on a tripod was tethered to a computer via a USB cable and controlled by software that makes use of the Canon SDK (Version 2.11). In each scene, the exposure step was set to 1/3 of a stop and a 5760 \( \times \) 3840 high resolution RAW image was acquired at each of the 55 possible shutter speeds. A 960 \( \times \) 640 low resolution JPEG image was also acquired from the live preview stream at each shutter speed.

A ground truth HDR image was constructed using all of the RAW high-resolution images in a benchmark (except if the image would only add noise such as being fully saturated) and compared against the HDR image constructed using only the RAW images selected by each method. HDR images were constructed using Photomatix Pro.\(^{3}\) We compare a method’s HDR image, referred to as the test HDR image, against a ground truth HDR image using the following performance measures.

- **Quality correlate.** The HDR-VDP-2.2.1 image quality metric, which quantifies the visual distortion of the test HDR image from the ground truth HDR image with a single quality score \(^{30,31}\).
- **Visual difference prediction.** The HDR-VDP-2.2.1 visual difference prediction metric, which estimates the probability at each pixel that an average human observer will detect a visually significant difference between the test HDR image and the ground truth HDR image \(^{30,31}\).
- **Mean squared error.** The mean squared error between the test HDR image and the ground truth HDR image.

Our experimental evaluation is the first to extensively evaluate existing state-of-the-art methods for image selection for stack-based HDR imaging, with significantly more methods, benchmarks, and performance measures being used compared to the limited numbers used in previous evaluations.

Figure 3(a) summarizes the quality of the test HDR images against the ground truth HDR images, as measured by the quality correlate, for the 105 HDR Photographic Survey benchmarks.\(^{http://www.rit-mcsr.org/fairchild_HDR.html\  https://www.hdrsoft.com/}\)
Figure 3(b) & (c) summarizes the errors for the 105 HDR Photographic Survey benchmarks. To measure errors, for each benchmark we summarize the probability at each pixel that an average human observer will detect a visually significant difference from ground truth with the percentage of pixels that are greater than or equal to 0.75; i.e., the percentage of pixels where a difference is very likely to be detected (see Figure 3(a)). As well, to measure errors, for each benchmark we summarize the mean squared error between the test HDR images and the ground truth HDR images (see Figure 3(b)). It can be seen that on these benchmarks, even with the limited range of choice in each benchmark—only nine images are available for selection, each a full stop apart—our set covering method achieves improvements across all three performance measures.

Figure 3 summarizes the results for the five Canon benchmarks. The (non-tonemapped) images encode the probability that an average human observer would detect a significant difference from ground truth: blue, $p = 0.0$; cyan, $p = 0.25$; green, $p = 0.50$; yellow, $p = 0.75$; and red, $p = 1.0$. It can be seen that on these benchmarks, with a more extensive range of choice in each benchmark—55 images are available for selection, each $1/3$ of a stop apart—our set covering method consistently achieves excellent results as measured by all three performance metrics. On these benchmarks, the existing state-of-the-art methods fail to fully capture the more challenging scenes, whereas our set covering method successfully captures the scenes.

The methods can also be compared using speed as the performance measure. The methods can be clustered into fast (Barakat et al. [7], Pourreza-Shahri and Kehtarnavaz [15], and our set covering), and slow (Hasinoff et al. [10], Seshadrinathan et al. [13]). A MATLAB implementation of our set covering method took approximately $2/3$ sec. for pixel classification for 55 images (Step 2) and $1/3$ sec. for image set selection (Step 3). In comparison, Hasinoff et al.'s [10] method took an average of 82.4 sec. The key reason for the speed and computational complexity differences between the fast and slow methods is that the fast methods place a threshold on acceptable SNR for each LDR image whereas the slow methods place the threshold on the final HDR image. The former allows fast greedy methods whereas the latter raises the computational complexity significantly (either known to be NP-complete or empirically shown to be high).

Finally, the methods can also be compared using the median and 75th percentile number of images selected across all 110 benchmarks: Barakat et al. [7], 4 and 4 images; Hasinoff et al. [10], 3 and 3 images; Pourreza-Shahri and Kehtarnavaz [15], 3 and 4 images; Seshadrinathan et al. [13], 1 and 2 images; and our proposed set covering method, 3 and 4 images, respectively. Thus, the improvement in accuracy of our proposed method is not at the expense of increasing the capture time for most scenes.

**Conclusion**

We proposed a method for selecting the set of images to combine in stack-based HDR imaging that is fast and offers improved accuracy. Our technique minimizes the set of images to combine, while ensuring that the resulting HDR image faithfully captures the scene’s irradiance. On 110 benchmark scenes, our proposed method gave improved HDR images as measured against ground truth using a pixel-based metric and two perception-based metrics. As well, our experimental evaluation was the first to extensively evaluate existing state-of-the-art methods for image selection for stack-based HDR imaging.
Figure 4. For various benchmark scenes, (a) ground truth HDR image (tonemapped), (b)–(f) visual representation of prediction of visually significant differences from ground truth [31], quality correlate (/100) [31], mean squared error, and number of images selected for various exposure selection methods: (b) Barakat et al. [7]; (c) Hasinoff et al. [10]; (d) Pourreza-Shahri and Kehtarnavaz [15]; (e) Seshadrinathan et al. [13]; and (f) our proposed set covering method. Best viewed in color; zoom in for additional detail.
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