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Joint Up-sampling High Dynamic Range Images with a Guidance Image

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Abstract. In this paper, we address the problem of acquiring guidance images for use in joint up-sampling of high dynamic range (HDR) images. A guidance image is usually an unprocessed high-resolution image that is indispensable to joint up-sampling, which is aimed at accelerating a large class of image processing operators. However, the guidance image is blank-posed in joint up-sampling of the HDR image, which involves the process where multiple low dynamic range (LDR) images with various exposure times in the same scene are synthesized into one image with a greater dynamic range; Such many-to-one operations limit joint up-sampling in being applied to this field. To this end, we propose an HDR guidance image (HGI), which is an image type generated by weighted averaging LDR images into a single with rich contour information. The huge advantage of joint up-sampling is that the cost of running the original algorithm is at a greatly reduced resolution. Since HGI synthesis takes about 3-70ms, and joint up-sampling of an HDR image takes about 20-300ms, most operations can be done with GPU shaders. Compared with the conventional methods of HDR image reconstruction, using joint up-sampling can achieve 3-10 times the performance acceleration. We demonstrate that joint up-sampling using our guidance images can produce high-resolution HDR images with no visible degradation compared to the image produced by the conventional method.

Keywords: High Dynamic Range (HDR); Guidance image; Up-sampling

AMS Mathematics Subject Classification (2010): 94A08, 62H35

1. Introduction

Research in joint up-sampling has yielded a variety of efficient methods [1-3] that accelerate a large class of image processing operators. Joint up-sampling can be applied to one-to-one image operators, in which the input and output image correspond one by one, such as enhancing detail [4-6], transforming the image by applying a master photographer's style[7,8], and eliminating the effects of atmospheric scattering [9,10].

The acceleration mechanism of joint up-sampling is approximating the local transformation model that contains the local maps between the low-resolution input/output pair, and then reintroducing details by applying the model to a guidance image (Figure 1). Unprocessed high-resolution images are commonly used as guidance images, which contain the image structure and especially contour information. Joint up-sampling has a strong dependence on contour information within guidance images [2]. In other words, the HGI must have clear contour information abstracted from the LDR images and a low noise level. Although both HGIs and HDR images are synthesized from LDR images, they are two completely different image types.

High dynamic range image reconstruction is a technique used in imaging and photography to reproduce a greater dynamic range of luminosity than is possible with standard digital imaging or photographic techniques. There are various methods of HDR image reconstruction. One classic reconstruction approach that has been widely used is recovering the HDR image from a set of LDR images with different exposure times by first linearizing the images using the inverse of the camera response function (CRF), and then averaging them into a single HDR image [11]. The reliability of every pixel measurement is accounted for by using a weighted average.

However, the algorithms of HDR image reconstruction cited in Section 2 do not appropriately consider the computational complexity, which limits the speed of HDR reconstruction, especially on mobile devices. Generally, an unoptimized reconstruction of a 12megapixel HDR image can take several hundred seconds, and post-processing operations further extend this time.

Joint up-sampling has proven to be an effective scheme for accelerating image operators, but joint up-sampling an HDR image from a low-resolution reconstruction is fundamentally blank-posed. For this problem, joint up-sampling is inapplicable because the guidance image has no unique input corresponding to itself. Recently, new up-sampling algorithms using neural networks have been proposed in [12-14] and have achieved state-of-the-art performance. The authors of [12] claim that the more complex image operators can be learned by neural networks, which are trained off-line from data, and therefore they do not require access to the original operator at the runtime. However, these methods suffer from the same weakness: training sets require data (input) and labels (output) to match one by one, but the data consists of multiple LDR images.

To tackle the above-stated problem, we propose a novel guidance image for use in joint up-sampling HDR images, called an HDR guidance image (HGI). Clear contour information and high image purity are necessary conditions for the guidance image [1]. According to this principle, the problem of up-sampling the HDR image is reformulated to HGI synthesis. Because using the weighted average in HDR image reconstruction can maximize the signal-to-noise ratio [11], we were inspired to introduce a well-designed weighting function in HGI synthesis. Although there are many similarities between HDR image reconstruction and HGI synthesis, directly applying the weighting functions used by HDR image reconstruction to HGI synthesis cannot achieve optimal results. In addition, observations show that the dark part of the guidance image is susceptible to noise pollution; therefore, we introduce a noisy level factor as weighting term, which results in a great enhancement in both Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Based on the GPU shaders, our algorithm can be easily deployed on the OpenGL-enabled platforms. Experimental results showed that our GPU approach was two orders of magnitude faster than the equivalent CPU implementation. Moreover, compared to the images produced by produced by the conventional method, it was demonstrated that joint up-sampling using the proposed guidance images could produce high-resolution HDR images with no visible degradation.

The remainder of this paper is organized as follows: In Section 2 we review the original process of HDR image reconstruction and joint up-sampling algorithms are briefly summarized. The method of HGI synthesis is presented in Section 3. Visual and quantitative results together with a discussion are given in Section 4. Finally, Section 5 concludes this paper.

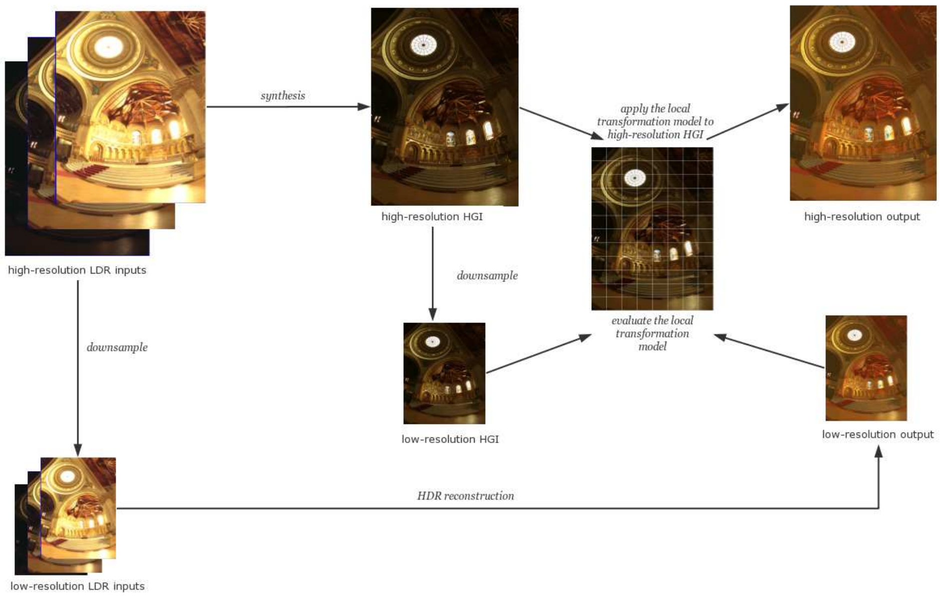


Figure 1: The flowchart illustrates the complete process of HDR joint up-sampling. First, high-resolution LDR inputs are compressed into low-resolution LDR inputs while HDR reconstruction is performed at low resolution. Then, the weighted average of the high-resolution LDR inputs is transformed into an HGI, which records edge information in a large dynamic range. Finally, joint up-sampling evaluates the local transformation model in a low-resolution HGI input/output pair, and applies it to the high-resolution HGI to obtain high-resolution output. The process of joint up-sampling is not affected by low-resolution image processing. In other words, low-resolution image processing is a black-box for joint up-sampling.

2. Related work

This work investigates HGI synthesis and draws inspiration from the various up-sampling algorithms. The effect of the weighting function in HGI synthesis is like that in HDR reconstruction. Therefore, in this section, as a first step to understanding HGIs, the theory of weighting function in HDR reconstruction is reviewed. Then, a variety of the typical joint up-sampling algorithms that have been currently proposed are reviewed in categories, and their features, as well as some related issues, are discussed.

2.1. Weighting function

Many schemes have been proposed for HDR image reconstruction [11,15-18]. In general, the HDR image is reconstructed in two steps: first, estimate the inverse of the camera response function (CRF) f^{-1} that maps a camera's output z to its inducing exposure Et,, where t is the exposure time; then, the HDR image that approximately corresponds to the real-world irradiance E (up to scale) is recovered. Specifically, the radiance map can be obtained by:

$$\hat{E} = \frac{\sum_i w(z_i)e_i}{\sum_i w(z_i)}, \text{ and } e_i = \frac{f^{-1}(z_i)}{t_i} \quad (1)$$

where $i = 1,2$ ...are the indexes over LDR images. Every method has its own weighting function $w(z)$. The purpose of the weights in (1) is to exclude saturated and noisy pixel intensities from the weighted average. Beyond that, post-processing for the radiance map is necessary, such as white balance, gamma correction, and tone mapping [19,20]. Figure 2 shows the general steps of HDR image reconstruction. Additional complexities arise when objects of the scene or camera move between shots, and thus images with different exposures should be deblurring [21].

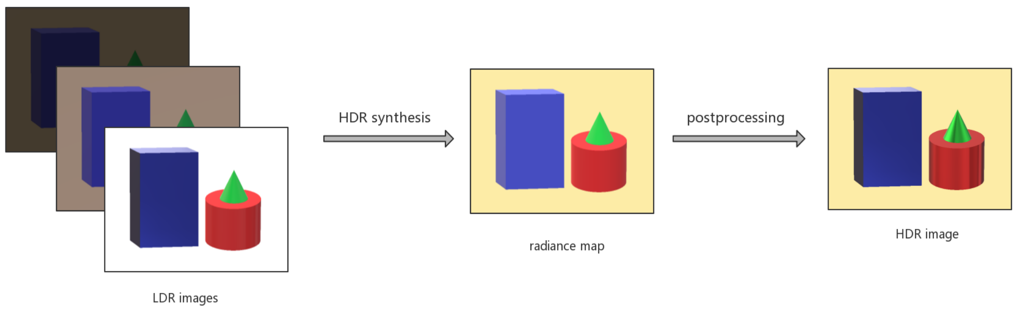


Figure 2: The traditional HDR image reconstruction approach. First, pixels in the LDR images are mapped to the scene radiances using CRF, and then the mapped LDR images are synthesized into a radiance map by a weighted average method. Finally, an HDR image can be displayed on the screen after a series of post-processing tasks.

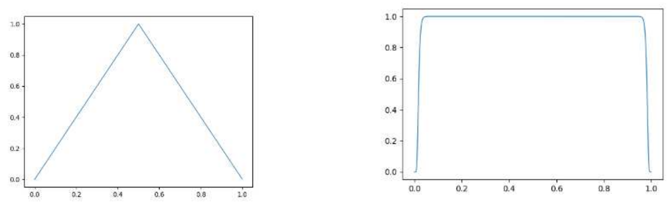
In the past decade, several weight functions for HDR image reconstruction have been proposed. Debevec and Malik [17] suggested a hat function (Figure 3(a)) that assigns higher weights to outputs in the middle of the camera dynamic range because they are the farthest from both the underexposed and saturated outputs. Because the points with large slope are regarded as unreliable, Mitsunaga and Nayar [18] proposed a method that assigns weights to the output according to the derivative of the inverse CRF. However, the hat function and derivative type function have proven to be far from optimal in terms of SNR [22]. With in-depth research, the noise model under the assumption of compound-Gaussian noise and exposure time have also been introduced into weighting functions [15,16], which results in the weight decreasing linearly with the digital output noise level, and increasing with the exposure time.

The weighting function used in HGI synthesis has some variations with HDR image reconstruction. First, the HGI only needs to eliminate the interference of the saturated and noise pixels; the transformation of CRF is not required. Secondly, some of the weight functions used to estimate the radiance map are too computational and difficult to deploy on the GPU platform. Considering this, the weight function proposed by Neve et al. [22]

was selected, which contains an extra denoising factor. The extra factor should be related to the noise level of the LDR images. However, in-depth research on this was not conducted by the author, and the factor was simply predefined as a constant 1. The reason for this is that noise estimation of a single image was a challenge before their article was published, especially for the images with rich textures.

Chen et al. [23] solved the related problem of noise estimation on a single image. They provided rigorous analysis of the statistical relationship between the noise variance and the eigenvalues of the covariance matrix of patches within an image. Their work solved the problem through eigen-decomposition of the covariance matrix, such as Principal Component Analysis (PCA).

For our method, the extra factor in Neve et al.'s function is replaced with the noise estimation term proposed by Chen et al. [23]. In the degenerate case where the extra factor is assigned with a constant of 1, our representation is equivalent to Neve et al.'s function. The proposed weighting function can extract more contour information from LDR images compared to the previous one. The synthetic HGI has low noise and clear contour information, which helps the joint up-sampling algorithms achieve better results.



(a) (b)

Figure3: Coordinate diagrams of two kinds of weight functions: (a) The hat function. (b) The weighting function proposed by Neve et al., who suggest $\gamma_i = 1, i = 1,2$ ...Compared with (a),(b) can keep the image structure from distortion and remove saturated pixels at the same time.

2.2. Joint up-sampling

Joint up-sampling the low-resolution processed image to the high-resolution output has received much attention. Prior work in this direction has been aimed at generating a high-resolution output given a low-resolution input and a high-resolution guidance image, such as joint bilateral up-sampling [3], guided image filtering [2], and bilateral guided up-sampling [1]. While those algorithms have made an outstanding contribution to the acceleration of image operators, joint up-sampling an HDR image still has a lack of research, and therefore we extend this approach to this area.

Joint bilateral up-sampling (JBU) [3] applies a bilateral filter to the high-resolution guidance image and low-resolution input to obtain a piecewise-smoothing high-resolution output. The implementation of this algorithm is simple. First, the low-resolution output is linearly interpolated to a high-resolution. Then, the high-resolution output is processed by the interpolating image and guidance image using bilateral filter. Such operations require a large amount of computational resources, and therefore many algorithms have been presented to accelerate the bilateral filter [24-26]. We chose to accelerate the JBU using the bilateral grid [25], which is a high-dimensional data structure that enables fast processing of the bilateral filter. In this method, images are expressed by homogeneous coordinates at a high dimension, and then they are divided into separate grids to execute the operations of the bilateral filter. The greatest advantage of this data structure is that most calculations in the bilateral grids are linear and can be parallelized in the GPU.

Guided image filter (GF) [2] works by fitting linear local transformation functions between overlapping local patches in the input image and a guidance image. This technique is applied to up-sample low-resolution noise reduction, HDR compression, and depth maps into high-resolution ones that respect color discontinuities of the real scene. The GF can perform as an edge-preserving smoothing operator like the bilateral filter, but it has better behavior near the edges. Besides smoothing images, the GF also has splendid effects on up-sampling.

Bilateral guided up-sampling (BGU) [1] fits an image operator with the grid of local transformation models on the low-resolution input/output pair. The high-resolution output is then generated by applying the local transformation model to the high-resolution input image. Compared to a GF, this method works well with the nonlinear image operator while achieving higher PSNR and SSIM.

This paper focuses on the acquirement and utilization of the HGI because all the details of the HDR reconstruction and post-processing are in a black box for the up-sampling process (Figure 1). In the case of using the HGI, the joint up-sampling of the HDR image has no difference to the one-to-one image operators. The advantages of the HGI include stronger applicability and generality, which can easily be extended to the various up-sampling algorithms that are supported by a guidance image.

3.The synthesis steps of the HGI

The purpose of the HGI is to provide a low-noise, edge-preserving guidance image for joint up-sampling. The HGI is acquired by combining LDR images, and each pixel in the HGI is the weighted superposition of the same coordinate in the LDR images. The weight makes the following contributions: 1): Eliminating saturated pixels outside the dynamic range of the camera. Overexposed or underexposed photographs often show large areas of light or dark. 2): Giving more weight to the images with lower noise. Images under low illumination usually have a lot of noise. In summary, the weight is measured by both the pixel value and the noise level of the image. At the same time, the weighting function should not weigh non-noise pixels; otherwise, the edge information may be lost. Considering the above, the weighting function in HGI and HDR image synthesis has several differences, and we chose the function proposed by Neve et al.[22] (Figure 3(b)):

$$w_j(z) = \gamma_j\, exp\left(-\frac{(z_j - z_{mid})^a}{b(z_{mid})^a}\right) \tag{2}$$

where z is a pixel intensity, with $z_{mid} = (z_{max} - z_{min})/2$, z_{min} and z_{max} are the boundary intensities of the image's dynamic range, respectively; j is the index of the LDR images; and each LDR image has its own factor $\gamma_j (j = 1,2, \dots)$. Experimentally, it was found that $a = 200$ and $b = 0.02$ gave a good trade-off between noise suppression and saturation consideration; however, these two parameters depend on the characteristics of the specific camera and can be adjusted. The flat interval of (4) increases with the value of a, and b affects the steepness of the function.

It was found that the extra factor γ_j in (2), which was assigned with a constant, was not the best solution because each picture in the LDR images has a different noise level. Hence, the original weighting function being used in the HGI had even worse characteristics than weighing the LDR images without the factor. The extra weighting factor γ_j was redefined for each LDR image and is given by:

$$\gamma_j = \frac{\sum_{i=1} \sigma_i - \sigma_j}{\sum_{i=1} \sigma_i} \quad (j = 1,2 \dots) \tag{3}$$

where σ is the noise standard deviation of LDR images. In the following section, a review is given of the estimation steps of noise variance σ^2 proposed by Chen et al. [23].

Given a multi-channel image I , with size $M \times N \times c$, it can be decomposed into a number of patches $X_s = \{x_t\}_{t=1}^{s}$, which contain $s = (M - d + 1)(N - d + 1)$ patches of size $d \times d \times c$ from the image I, and x_t is rearranged into a vector with size $r = cd^2$.. Then, the eigenvalues of the covariance matrix $\Sigma_x = \frac{1}{s}\sum_{t=1}^{s}(x_t - \mu)(x_t - \mu)^T$ with $\mu = \frac{1}{s}\sum_{t=1}^{s} x_t$ are calculated. Finally, the noise variance σ^2 is acquired by finding the median of the eigenvalues of Σ_x. Table 1 shows the pseudo-code that estimates the noisy standard deviation σ.

Require: The Observed Image $I \in R^{M \times N \times c}$
1: Generating dataset $X_s = \{x_t\}_{t=1}^{s}$
2: $\mu = \frac{1}{s}\sum_{t=1}^{s} x_t$
3: $\Sigma = \frac{1}{s}\sum_{t=1}^{s}(x_t - \mu)(x_t - \mu)^T$
4: Calculating the eigenvalues $\{\lambda_i\}_{i=1}^{r}$ of the covariance matrix Σ with $r = cd^2$ and order $\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_r$.
5: **for** $i = 1 : r$ do
6: $\tau = \frac{1}{r-i+1}\sum_{j=i}^{r} \lambda_j$
7: **if** τ is the median of the set $\{\lambda_i\}_{j=i}^{r}$ **then**
8: $\sigma = \sqrt{\tau}$ and break
9: **end if**
10. return noisy level estimation σ.

Table 1: Estimation steps of image noise standard deviation.

Finally, the HGI is recovered as follows:

$$\hat{z} = \frac{\sum_j w(z_j) z_j}{\sum_j w(z_j)} \tag{4}$$

which is a pixel-wise weighted average of the pixel values in the different LDR images. Formula (4) is essentially a variant of Formula (1). Figure 4 shows the differences between the HDR image and the HGI, which reflect on the local contrast, brightness, and even color orientation. The HGI can express contour information more fully, which is the necessary requirement of joint up-sampling.

4. Experiment

In this section, the joint up-sampling results of the HDR image are described. The HDR image was up-sampled by synthesizing LDR images into the HGI and then applying joint up-sampling to the HGI to acquire the high-resolution output, as illustrated in Figure 1. Both BGU and GF require the low-resolution HGI to fit the local transformation model, which records the local map of the low-resolution input/output pair and then applies the model to the high-resolution HGI. The implementation of JBU is as follows: First, the low-resolution output is enlarged to a high resolution. Then, the scaled output is filtered with the high-resolution HGI by using the bilateral filter. For this study, because it was sufficient for the experimental requirements, simple linear scaling was used to compress the high-resolution HGI or enlarge the low-resolution output. Both PSNR and SSIM served as the evaluation metric (a higher value was better) because the single metric PSNR is known to have limited correlation with perceptual image fidelity [27].

Figure 4: Local enlargement of the HGI and HDR image. Clear contour information of the HGI facilitates the up-sampling process.

The proposed method was evaluated, including HGI synthesis and joint up-sampling, on a laptop CPU and GPU. The GPU consisted of the NVIDIA GeForce MX150, NVIDIA GeForce GTX 1060, and AMD Radeon RX 480 graphics cards, which feature unified shaders. The CPU was an Intel Core i7 8700 (3.4 GHz processor and an 8 MB cache). In developing the HGI, a major goal was to facilitate parallelization on graphics hardware. The benchmarks showed that on a CPU, the bottleneck lied in the weighted mean stage where the cost was dominated by a pixel number. We took advantage of hardware texture units on the GPU to efficiently perform weighted averaging.

First, the benchmark varied the image size while keeping the patch size of noise estimation parameters constant (d =8,$c = 3$). The same LDR images were used at various resolutions, as shown in Figure 5. In addition, the average runtime was recorded over five iterations at the same resolution. Table 2 illustrates that the runtime of HGI synthesis was linear in the image size, and ranged from 2.3ms to 72.6ms on the GTX1060. On the CPU platform, multi-threading technology was used to synthesize the HGI based on the OpenCV. For comparison, the CPU implementation ranged from 170ms to 5s on the same inputs. In contrast, desktop GPU platforms had a batter performance, which is related to the pipelines and clock frequencies. The HGI on was synthesized on the GPU through off-screen rendering, which was executed on the core mode of OpenGL 4.5, using only a simple vertex shader and fragment shader. The testing code can be downloaded from https://github.com/hans8638/HGI.

Exposuretime=1/25s
ISO=800
Noise level=1.72

Exposure time=1/6s
ISO=800
Noise level= 2.30

Exposure time=1s
ISO=800
Noise level= 3.27

Figure 5: A series of LDR images and their partial enlarged detail. The exposure times were: 1/25, 1/6, and 1 s. Shot by a Canon PowerShot G1X

Resolution	MX150	GTX1060	RX480	CPU
800*600	8.2ms	2.3ms	3.1ms	170.2ms
1024*768	11.7ms	3.5ms	3.8ms	237.5ms
1280*960	21.2ms	6.1ms	5.9ms	326.5ms
1440*1080	27.3ms	7.8ms	7.4ms	416.8ms
1680*1260	34.6ms	10.2ms	11.3ms	695.0ms
1920*1440	47.5ms	13.5ms	12.4ms	731.9ms
2560*1920	89.4ms	25.7ms	23.8ms	1562.7ms
4352*3264	241.2ms	72.6ms	67.6ms	5023.2ms

Table 2: The synthesis time of the HGI under the mainstream resolutions. By contrast, desktop platforms had the best performance, which is related to the pipelines and clock frequencies

Next, the original HDR construction method proposed by Granados et al. [11] was compared with the joint up-sampling method from Section 3 using a series of LDR images shown in Figure 5. Figure 6 shows that there was no visual difference between the two approaches. From the local enlargement, the joints of the light box were restored well, in addition to the texture of the wall being very clear. A striking acceleration was also obtained: for the original HDR reconstruction 5.8 s was needed within LDR images under 4352×3264 pixels, whereas in the case of BGU using the HGI only 241.2ms was needed for estimation (GTX1060). For the quality parameters, BGU achieved 38.53 dB in PSNR, which was an improvement over GF by 0.58dB and JBU by 5.33dB. We suggested using BGU as the preferred algorithm for joint up-sampling because it has a stronger image local transformation fitting ability and a shorter processing time. To improve the reliability of the experiment, a test set containing 30 sets of LDR pictures was made, which included most exposure models in real life. Figure 7 shows some of the experimental results.

Groundtruth	JBU	GF	BGU
	PSNR= 33.197819	PSNR = 37.946282	PSNR=38.532046
	SSIM = 0.958972	SSIM = 0.977612	SSIM=0.983086
Time=5.8s	Time=1.76s	Time=2.5s	Time=320ms

Figure 6: Qualitative results among the three joint up-sampling algorithms. For each method, the high-resolution output and partial enlarged details are shown. The ground truth was obtained by Granado et al.'s method and processed by tone mapping.

5.Conclusion

We presented an image type for use in the joint up-sampling of an HDR image, called HGI. The new image type is aimed at efficiently generating high-resolution output with a low-resolution input and an HGI. By weighted averaging the LDR images into one image, the contour information of real scene can be fully extracted and the additional noise level term can be helpful in improving the accuracy of up-sampling. The high-speed synthesis of the HGI on GPU was realized, which paves the way for mobile applications. Experiments showed that the proposed HGI could achieve the excellent visual performance while requiring 3-10 times less the computational time cost. Obviously, BGU had the best parameter performance among the three up-sampling methods in the experiment, while maintaining a shorter running time; therefore, we recommend BGU as the preferred method of up-sampling. Neural networks up-sampling has a great advantage in learning local transformations between input/output images, but our article did not investigate the application of HGI in such algorithms. In the future, we plan to develop HGI in this direction and hope more researchers can participate in it.

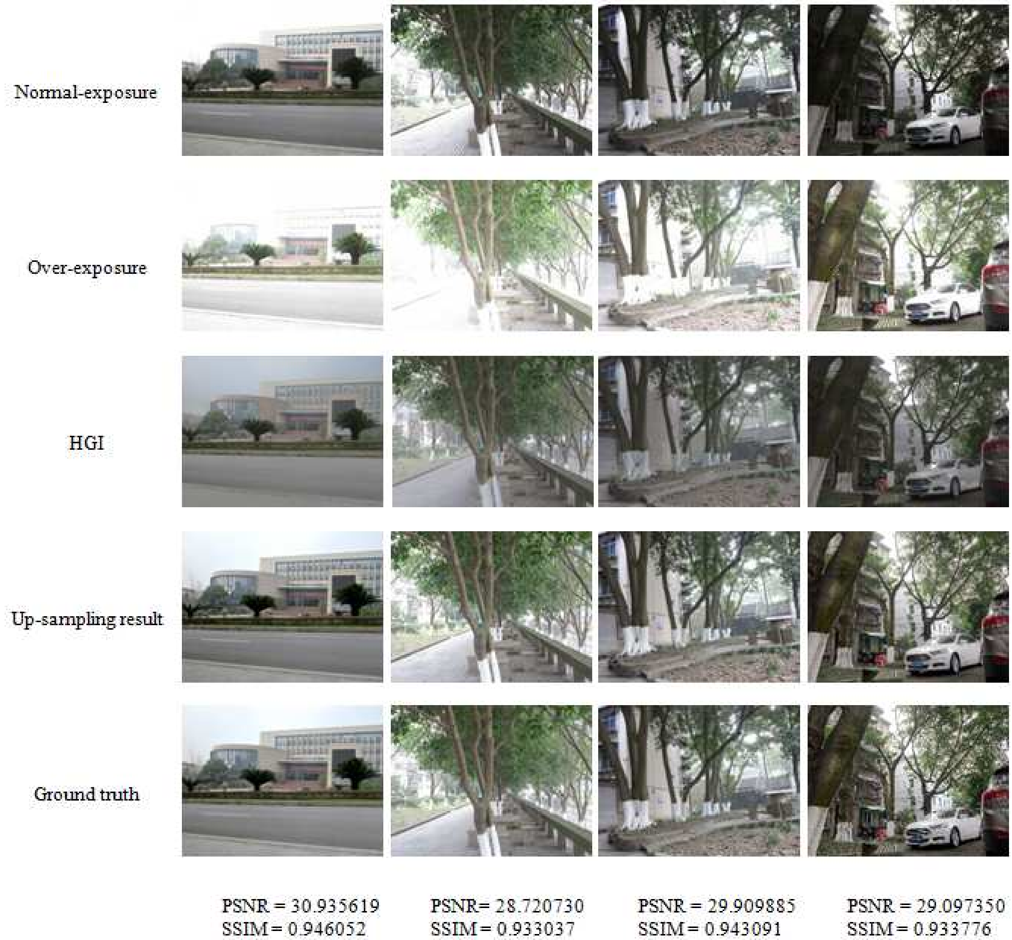


Figure 7: Some qualitative results on images from our test set. The unified up-sampling algorithm adopted in this experiment was BGU. The order from top to bottom is an under-exposed image, a normal-exposed image, an over-exposed image, the HGI, the joint up-sampling result, and the ground truth.

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