Boosting Laplacian Pyramid for Exposure Fusion

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ABSTRACT

The dynamic range of a natural scene often spans a much larger scope than the capture range of common digital cameras. An exposure image only captures a cer¬tain dynamic range of the scene and some regions are invisible due to under-exposure or over-exposure. Vari¬able exposure photography captures multiple images of the same scene with different exposure settings of the camera while maintaining a constant aperture. In order to recover the full dynamic range and make all the details visible in one image, high dynamic range (HDR) imaging techniques are employed to reconstruct one HDR image from an input exposure sequence. These generated HDR images usually have higher fidelity than convectional low dynamic range (LDR) images, which have been widely applied in many computer vision and image processing applications, such as physically-based realistic images rendering and photography enhancement. On the other hand, the current displays are only capable of handling a very limited dynamic range.

This Project proposes a new exposure fusion approach for producing a high quality image result from multiple expo¬sure images. Based on the local weight and global weight by considering the exposure quality measurement be¬tween different exposure images, and the just noticeable distortion-based saliency weight, a novel hybrid expo¬sure weight measurement is developed. This new hybrid weight is guided not only by a single image's exposure level but also by the relative exposure level between dif¬ferent exposure images. The core of the approach is our novel boosting Laplacian pyramid, which is based on the structure of boosting the detail and base signal, respec¬tively, and the boosting process is guided by the proposed exposure weight. Our approach can effectively blend the multiple exposure images for static scenes while pre¬serving both color appearance and texture structure. Our experimental results demonstrate that the proposed ap¬proach successfully produces visually pleasing exposure fusion images with better color appearance and more tex¬ture details than the existing exposure fusion techniques and tone mapping operators..

1. INTRODUCTION

Exposure fusion is currently a very active research area in the field of computer vision, as it offers the full dynamic range from an input exposure sequence. The task of exposure fusion is slightly different from the traditional HDR imaging technique , and it does not need to reconstruct a single HDR image from a set of images under different exposure settings from the same

scene . The traditional image fusion techniques are most relevant to our algorithm, but image fusion algorithms focus on preserving the details and can be viewed as an analogy to alpha blending . The purpose of exposure fusion is to acquire the full dynamic range of a scene by blending multiple exposure images into a single high-quality composite image, and preserving the detail and texture information as much as possible.The general image fusion approaches usually use the multisensory or multispectral images as input while exposure fusion methods use the multiple exposure images as input. Taking a sequence of images with different exposures of a scene as input, our approach produces a detail and texture preserving fusion result using the boosting Laplacian pyramid. The proposed fusion method neither needs to generate any HDR image nor needs to do the tone mapping process.

RELATED WORK:

In recent years, a few approaches of multiple exposure fusion have been proposed and are widely used for their simplicity and effectiveness. Mertens et al. presented an exposure fusion approach using Gaussian and Laplacian pyramid in a multiresolution fashion, which belongs to the pixellevel fusion approach. Raman and Chaudhuri employed the edge-preserving bilateral filters to generate an exposure fusion result from multiexposure input images. Raman et al further proposed an automatic multiexposure fusion approach without the ghost artifacts by determining the moving objects. Recently, Zhang and Cham presented a tonemapping-like exposure fusion method under the guidance of gradient-based quality assessment. Later, Song et al synthesized an exposure fusion image using a probabilistic model,
which preserves the luminance levels and suppresses reversals in the image luminance gradients. More recently, Hu al presented a novel registration and fusion approachfor the exposure images in the presence of both live scenesand camera motions.Compared with the traditional tone mapping techniques, the proposed exposure fusion approach does not need to recover the camera response curve and record the exposure time of an input sequence of different exposure images . As described earlier, the conventional two stages include the HDR image creation and tone mapping, and this two-stage process usually needs complex user

interactions and tends to miss some color and texture details in the created fusion result. Therefore, it is desirable to produce the fusion result from a multiple exposure sequence input, which is more efficient and effective. The purpose of our exposure fusion technique is to directly produce visually pleasing photographs for the displaying purpose while preserving the details and enhancing the contrast.

EXPOSURE FUSION ALGORITHM
Proposed Method Block diagram:

Block Diagram:

Exposure Fusion is a fairly new concept that is the process of creating a low dynamic range (LDR) image from a series of bracketed exposures.In short, EF takes the best bits from each image in the sequence and seamlessly combines them to create a final 'Fused' image. Or more technically, the fusing process assigns weights to the pixels of each image in the sequence according to luminosity, saturation and contrast, then depending on these weights includes or excludes them from the final image. And because Exposure Fusion relies on these qualities, no exif data is required, and indeed, if you wanted to, you could include an image with flash to bring darker areas to life.Exposure Fusion also has one other trick up its virtual sleeve. It can also create extended Depth Of Field images by fusing together a sequence of images with different DOFs. This could actually be quite handy, say if lighting conditions at the time don't allow the full DOF to be captured in one shot, or if you're just limited by the DOF of your lens. This process could also be used creatively to get different DOFs in one image.
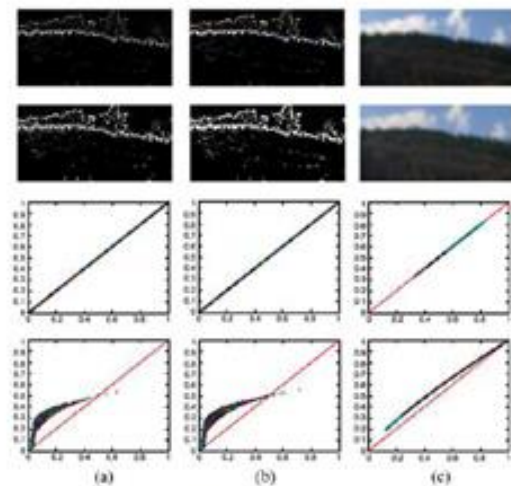
Fig. 3. Magnitude of the RGB color vector in the base layers and the detail layer is boosted along the direction of the RGB color vector. Top row: before boosting. Second row: after boosting. Third row: direction of the RGB color vector. Bottom row: magnitude of the RGB color vector. (a) Level 0. (b) Level 1. (c) Level 2.

Exposure fusion algorithm:

Our goal is to automatically find the useful visibility information from each input exposure image, and then combine these regions together so as to generate a high quality fusion result with more details. We propose three different guidance methods to identify each pixel's contribution to the final fusion components, and we consider both the global and local exposure weight for multiple exposure fusion. Our method is different from the approach in [23], which emphasizes the local cues to determine the weight maps, such as the contrast, saturation and exposure measurement. In contrast, we measure the exposure weight by computing the exposure levels from both the local and global information.

A. Local exposure weight:

This exposure quality assessment $Q(x, y)$ sets the lightest and darkest regions with zero values, while it assigns otherregions with the values between zero and one. Our exposure weight map $E(x, y)$ is the grayscale image of $Q(x, y)$ and represents the exposure quality of the input image ;

B. Global exposure weight:

The aforementioned exposure weight is a local weight map, which computes the exposure level only from a single exposure image of the input sequence. However, this local weight map does not utilize the global relationship of measuring the exposure level between different exposure images. Hence we define a global exposure weight $V(x, y)$ to make a better exposure measurement by considering other exposure images from the sequence.

C. JND-Based Saliency Weight:

JND refers to the maximum distortion that the human visual system (HVS) does not perceive, nd defines a perceptual threshold to guide a perceptual image quality measurement task. The JND model helps us to represent the HVS sensitivity of observing an image [12]. It is an important visual saliency cue for image quality measurement. We employ the JND model to define the saliency weight $J(x, y)$, which can pick up the pixels in different exposure images with good color contrast and saturation regions. Furthermore, we can utilize a saliency weight map based function to estimate the level of boosting in our BLP.

Boosting Laplacian Pyramid:

Our boosting process is guided by the aforementioned local exposure weight and JND-based saliency weight with different exposure images. It is very useful tocorrectly select the salient regions to boost, and the boostinglevel is controlled by the exposure quality measurement.In order to avoid the color casting artifacts, we multiplythe RGB triplet by a scalar, which keeps the chromaticityunchanged before and after signal boosting and reduces thecolor distortion. Fig. 3 gives an illustration of our boosting onthe magnitude of the RGB color vector along the direction ofthis color vector. The direction of the RGB color vector lies inthe line of 45 degrees diagonal, which means that the directionof this color vector does not change before and after using ourboosting Laplacian pyramid (Fig. 3, third row). At the sametime, the magnitude of the RGB color vector

increases nonlinearlybefore and after the boosting process (Fig. 3, bottomrow). Our boosting method preserves the structure and texturedetails so as to get a natural and visually pleasing fusion result.

Fig. 3. Performance comparisons on the input sequence with the exposure fusion approach [19] and the gradient directed fusion approach [27]. (a) Input sequence. (b) Result by [19]. (c) Result by [27]. (d) Our result. (e) Close-up of (b). (f) Close-up of (c). (g) Close-up of (d).

The detail layer is obtained by the original signal subtracting the Gaussian pyramid signal, which is based on the standard image Laplacian pyramid [1]. Our BLP exhibits the new advantages of boosting the base layer and detail layer signal according to the boosting guidance, which is computed by our local exposure weight and JND-based saliency weight introduced in Section III.

Boosting guidance:

As mentioned before, our boosting process is guided by the two image quality measurements, the local exposure weight guidance and the JND-based saliency weight guidance. We first use the exposure weight guidance to select the well exposed regions which need to be boosted using our BLP. This strategy can avoid the visual artifacts. It is beneficial to boost the base layer and detail layers with different extents for each pixel according to the guidance map, since the wellexposure regions and under-exposure or over-exposure regions of the sequence should be enhanced with different amplifying values during the boosting process.

Experimental Results:

These three weights indicate different aspects of image quality measurements, and the hybrid weight maps denote the overall contribution of the different exposure images to the final fusion result. As mentioned before, the basic principle of exposure fusion is to select the good exposure pixels from the input images, and preserve the detail and texture information as much as possible during the fusion process. Therefore, we define a local weight $E(x, y)$ and a global weight $V(x, y)$ to measure the exposure level of the input images. $E(x, y)$

selects the good exposure pixels while $V(x, y)$ eliminates the bad exposure regions of the current image. Thus, $V(x, y)$ helps $E(x, y)$ to compensate the exposure level measurement. $J(x, y)$ measures the visual saliency according to the background luminance and texture information.

CONCLUSION:

This paper has presented a novel exposure fusion approach using BLP to produce a high quality image from multiple exposure images. Our novel BLP algorithm is based on boosting the detail and base signal respectively, and can effectively blend the multiple exposure images for preserving both color appearance and texture structures. We therefore believe that our fusion method will suffice to produce the results with fine details for most practical applications. The comprehensive perceptual study and analysis of exposure fusion algorithms will make an interesting subject for future work. For instance, we can create a benchmark of input exposure images and conduct a user study to compare a representative number of state-of-the-art exposure fusion methods.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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