MRF-based High Dynamic Range Image Generation

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***Abstract*—Image enhancement using high-dynamic range (HDR) images is widely exploited; however, it is limited by detail loss and excessive color generation. In addition, capturing HDR images by commercial digital cameras is problematic. In this paper, we propose an image enhancement technique of fusing two images with different exposures. In order to reduce unnatural color changes in the fused image, initially we modify the lightness of the less-exposed image according to that of the highly exposed image. Then, we design a Markov random field model (MRF) by considering a gradient, chrominance, and smoothness constraint. Further, the MRF model is optimized via belief propagation. Experimental results show that the proposed algorithm generates more natural results than other state-of-the-art algorithms.**

Keywords— Image enhancement; High dynamic range image; Markov random field; Image fusion.

I. INTRODUCTION

In general, commercial digital cameras are not able to capture scenes as humans see. In many cases improper camera settings often lead to this problem, but the limited dynamic range of digital cameras is the primary reason. The scene luminance, which humans are able to perceive, varies between 10^{-3} and 10^{5} cd/m^2; however, the dynamic range of an ordinary digital camera is only about 10^2 [1].

When capturing such scenes with low exposure, textures are accurately captured in brighter regions while they are noisy or lost in darker regions, and vice versa. In particular, the main factors of this problem are low-dynamic range (LDR) and bit depth for grey level representation.

In order to improve the visual quality of such images, various image enhancement methods have been proposed and used in many applications, e.g., contrast enhancement, noise reduction, and distortion compensation. In particular, image enhancement modifies the quality of LDR images for better human visual perception.

However, original texture reconstruction is challenging since LDR images do not possess sufficient data in many cases. Therefore, high-dynamic range (HDR) imaging takes center stage. Compared to LDR imaging, HDR imaging uses wider dynamic range, larger bit depth, and higher fidelity [2]-[5]. Such advantages make HDR imaging practical in numerous applications, e.g., contrast enhancement and backlight compensation. HDR images can be acquired from multiple photographs and computer graphics, or with a multiple exposure sensor [4], [6].

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Since the display devices which can cover HDR images are not common, the HDR images have to be compressed again into LDR images via tone mapping. The main goal of tone mapping is to preserve texture details without distortion. To this end, various approaches have been proposed in the last decade.

These approaches can be divided into local and global algorithms. The global algorithms use the same tone mapping curve to every pixel and compress the dynamic range with lower time and space costs [7], [8]. Although they are successful in solving tone reproduction, the output images tend to be lack of texture details. Unlike the global algorithms, the local algorithms adopt different tone mapping curves to each pixel and operate by taking its surroundings [16], [17]. They improve local details and contrast; however, excessive visual deterioration can be induced.

In this paper, to solve such problems, we propose an image fusion method using Markov random field (MRF). Our method takes two differently exposed images as inputs; then we effectively combine them while preserving details. In order to take natural color changes into account, we also introduce lightness matching, color mapping, and global tone mapping.

II. IMAGE ENHANCEMENT

As mentioned in Sec. I, many algorithms related to image enhancement have been studied. In this section, we give a brief coverage of such algorithms sharing some similar features with our method. They can be categorized into either LDR or HDR image-based algorithms.

A. LDR Image-based Algorithm

Histogram stretching and equalization are widely used for visual quality enhancement of LDR images. These methods provide reliable results while excessive changes can be induced sometimes. Hence, various alternative algorithms have been proposed, minimizing excessive changes.

Menotti *et al.* have proposed a contrast enhancement algorithm which exploits bi-histogram equalization [9]. They decompose an input LDR image into several sub-images, equalizing each sub-histogram. This method achieves natural visual quality at the cost but less enhancement in contrast. Sengee *et al.* also have proposed bi-histogram equalization using a neighborhood metric [10]. For further improvement, this method divides large histogram bins into several sub-bins, arranging the intensity of the original LDR image with considering the neighbors. In addition, they reduce unnatural changes by equalizing two sub-histograms from a histogram average.

Kim *et al.* have adopted gain-controllable clipped histogram equalization for brightness preservation and detail enhancement [11]. They calculate the clipping-rate with consideration of averaging brightness; then thresholds are estimated from the rate. Tsai *et al.* have used a piecewise linear transformation in the HSV color domain to avoid non-linear approaches of histogram equalization [12].

Although the above algorithms provide reliable results, they are limited by less detail in input LDR images.

B. HDR Image-based Algorithm

HDR image-based enhancement takes center stage as an alternative to LDR image-based approaches due to the capturing of detail textures over a dynamic range wider than LDR. The key is to effectively compressing HDR to LDR while preserving texture details. For tone mapping, global and local approaches exist as mentioned in the introduction section.

Global approaches adopt a spatially invariant mapping curve [13]. Drago *et al.* have developed logarithmic compression imitating the human response to light, proposing improved gamma correction for contrast enhancement in dark regions [14]. Larson *et al.* have introduced a histogram adjustment technique based on the population of local adaptation. They consider contrast and color sensitivities to match viewing experience [15].

In general, global approaches are speedy and fabricate natural results. However, they provide lower visual qualities than local approaches which use spatially variant mapping curves. Reinhard *et al.* have applied scaling which is analogous to exposure information. Moreover, dodging-and-burning is included to accomplish tone reproduction [16]. Goshtasby have proposed a tone mapping algorithm which divides input images into uniform blocks and maximizes entropy in each block [17]. Nevertheless, this approach can cause block and boundary artifacts due to the adoption of regular blocks, especially relatively large blocks. Wang *et al.* have adopted adaptive local regions for revealing details while maintaining overall impression of inputs [18]. They used local tone and color mapping based on the adaptive local regions.

Recently, Jinno *et al.* estimate irradiance for each pixel and evaluate displacement and saturation via maximum a posteriori (MAP) estimation. In addition, they proposed a weighting scheme for HDR image generation [19]. Cvetkovic *et al.* have developed a tone mapping function using knee and gamma reproduction for enhancing visibility of details [20].

III. IMAGE FUSION USING MRF

Although HDR image-based algorithm shows higher quality results than LDR, generating a radiance map for commercial digital cameras is inefficient. Further, local tone mapping can induce unnatural color changes. Thus, we propose an image fusion algorithm with lowly-exposed (I_L) and highly-exposed (I_H) images to solve such problems.

Fig. 1 shows the overall procedure of the proposed algorithm. The arrows in the boxes represent relative dynamic range and bit depth of each image. The proposed system matches lightness of two input images and fuses them via a MRF model for texture detail enhancement. Finally, we conduct color mapping and global tone reproduction.

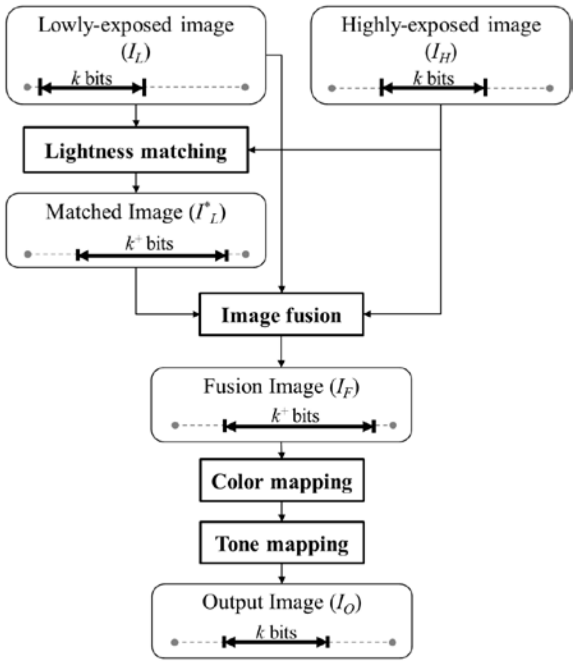


Fig. 1. Process flow of the proposed system.

We generate a fusion image I_F with I^*_L and I_H. In order to preserve and enhance texture details, we selectively bring high contrast textures from I^*_L and I_H. It can be regarded as a labeling problem for assigning a label s to each pixel of I_F. The label has two components. In particular one represents the selected image as $s = \{Low, High\}$. The other is a set S for labeling of the pixels in I_F in terms of the labels in s. We use the information of I_L instead of I^*_L for image fusion, since I_L has more accurate gradient information than I^*_L. By applying the Bayes rule, the posterior probability of S is written by

$$P(S \mid I_L, I_H) = \frac{P(I_L, I_H \mid S)P(S)}{P(I_L, I_H)} \quad (1)$$

where $P(S)$ is the prior probability of the labeling set S. $P(I_L, I_H|S)$ is the conditional probability density function of I_L and I_H given S. $P(I_L, I_H)$ is ignorable since unknowns are contained; this is a constant when I_L and I_H are given. Therefore, the MAP is equivalently found by

$$\max_F \{P(I_L, I_H \mid T)P(S)\} \cdot \quad (2)$$

Since we design a model of S via the MRFs, the posterior probability $P(S|I_L, I_H)$ can be characterized by the Gibbs distribution as

$$P(S \mid I_L, I_H) = \frac{1}{Z} \exp\left\{ \frac{-U(S \mid I_L, I_H)}{T} \right\} \tag{3}$$

where U, Z, and T denote energy function, normalization constant, and temperature, respectively. Consecutively, MAP estimation can be replaced by the minimization problem of the energy function U.

$$\min_F \{U(I_L, I_H \mid S) + U(S)\} \tag{4}$$

In order to define a likelihood energy funtion, we use not only gradient information but also magnitude values of chroma components. In general, well-exposed regions have larger gradient values and more vivid colors than over- or under-exposed regions. Based on such characteristics, the likelihood energy function is defined as

$$U(I_L, I_H \mid S) = w_l \sum_i \sum_{j \in N_i} 2^{k+1} - V_l(i,j)$$
$$\text{where} \quad V_l = \begin{cases} 2^{k+1} & |L_{Si}(i) - L_{Si}(j)| < Th \\ grad_{Si}(j) + \max(|a_{Si}(j)|, |b_{Si}(j)|) & otherwise \end{cases} \tag{5}$$

where N_i represents neighbors of i. Specifically, we use a 10×10 block to define N_i. S_i means the selected label at i while $L_{Si}(i)$ stands for the lightness value at i in the image of I_{Si}. In the same manner, a and b represent chroma components in the CIELab domain. Since regular blocks cause errors around object boundaries, we consider lightness distance by taking only the samples whose lightness difference is smaller than Th in V_l. *grad* is a gradient value calculated using the Sobel filter, and w_l means a weighting factor for likelihood energy.

To increase the accuracy of our solution, we use prior information in which physical properties in neighborhood of images present some coherence and do not change abruptly except at boundaries. We regard the labeling set as piecewise constant; thus its prior model can be characterized by the multilevel logistic as

$$U(f) = w_p \sum_i \sum_{j \in N_{4i}} 2^k - V_p(i,j)$$
$$\text{where} \quad V_p = \begin{cases} 2^k & |L_{Si}(i) - L_{Si}(j)| < Th \\ 2^k[1 - \delta(S_i, S_j)] & otherwise. \end{cases} \tag{6}$$

$U(f)$ penalizes the labels which has different values than 4-connected neighbors, N_4. If S_i is equal to S_j, $\delta(S_i, S_j)$ returns one, otherwise it returns zero. w_p means a weighting factor for prior energy.

Belief propagation (BP) is used to infer the optimized S for I_L and I_H. BP is an iterative inference algorithm which propagates messages in the pre-defined grid. In Fig. 2, the circle vertices are hidden values to be estimated while the rectangular vertices are observed values.

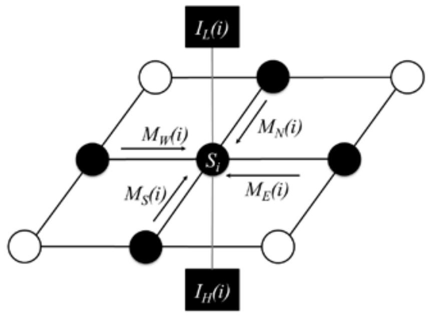


Fig. 2. Local message passing in image grids.

S_i possesses I_L and I_H states, receiving messages from four neighbors. Each message can be expressed as

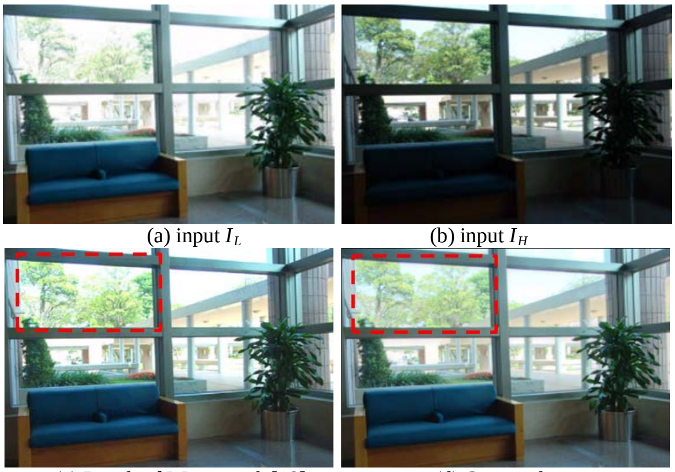
$$\begin{aligned} M_X^m(f_i) = \min_{f_X}[& w_n(X,i) \cdot w_p \cdot \{2^k - V_p(i,X)\} \\ & + \sum_{j \in N_X} \{grad_{f_X}(j) + \max(|a_{f_X}(j)|, |b_{f_X}(j)|)\} \\ & + \sum M_X^{m-1}(f_X)] \end{aligned} \tag{7}$$

where m and X denote the number of iteration and the pixels in the current direction among four directions, respectively. After 20 iterations, we select the final set S which has the minimum energy states.

IV. Experimental Result

In order to evaluate the performance of the proposed algorithm, a series of experiments were performed. We compared the performance of the proposed algorithm to other state-of-the-art algorithms: Gelfand *et al.* [5] and Wang *et al.* [18]. Fig. 3 and Fig. 4 show the input image pair, Wang's results, and our results for comparison. We used the same test images that Wang *et al.* used. Both methods are successful in revealing details; our algorithm provides more natural and vivid images while Wang's algorithm generates excessive color in the red box as in Fig. 3. In the case of an extreme HDR in Fig. 4, our proposed method preserves texture details rather than Wang's method.

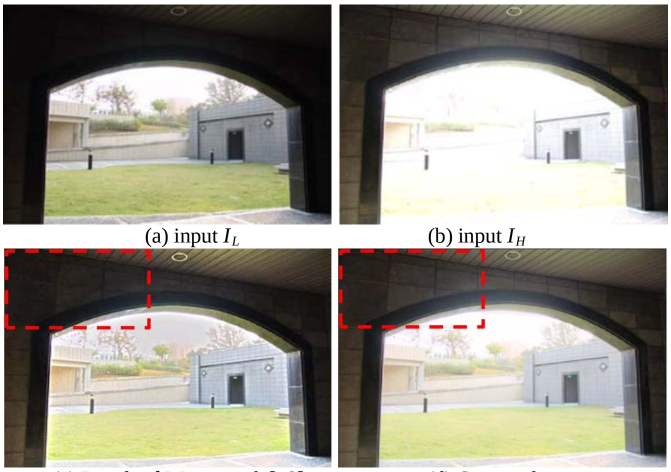
Further, our method demonstrates satisfactory subjective results for backlight compensation. Fig. 5 shows the experimental results of backlight compensation. We compared the proposed algorithm to Gelfand's method. In the results, while the conventional method loses texture details of leaves, our method successfully reveals that of leaves and person with vivid colors.



(a) input I_L (b) input I_H

(c) Result of Wang *et al.* [18] (d) Our result

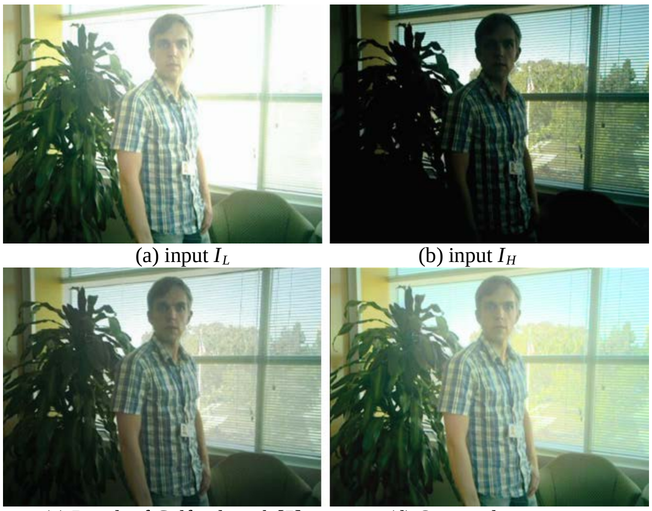
Fig. 3. Comparison of the results obtained by our method and by Wang's method.



(a) input I_L (b) input I_H

(c) Result of Wang *et al.* [18] (d) Our result

Fig. 4. Comparison of the results in the extreme HDR case



(a) input I_L (b) input I_H

(c) Result of Gelfand *et al.* [5] (d) Our result

Fig. 5. Backlight compensation

V. CONCLUSION

In this paper, we proposed an image fusion technique using an MRF model to enhance visual quality of images captured by ordinary digital cameras. With low and high exposed images, we adjust their luminance values and fuse them using global optimization. Experiment results show that the proposed algorithm generates more natural results than other state-of-the-art algorithms.

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