Image Contrast Enhancement Using Color and Depth Histograms

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***Abstract*—In this letter, we propose a new global contrast enhancement algorithm using the histograms of color and depth images. On the basis of the histogram-modification framework, the color and depth image histograms are first partitioned into sub-intervals using the Gaussian mixture model. The positions partitioning the color histogram are then adjusted such that spatially neighboring pixels with the similar intensity and depth values can be grouped into the same sub-interval. By estimating the mapping curve of the contrast enhancement for each sub-interval, the global image contrast can be improved without over-enhancing the local image contrast. Experimental results demonstrate the effectiveness of the proposed algorithm.**

***Index Terms*—Contrast enhancement, depth image, histogram modification, histogram partitioning.**

Fig. 1. (a) The color image $Teddy$ and (b) its depth image obtained by [10].

I. Introduction

IMAGE contrast enhancement techniques have been extensively studied in the past decades. Among various contrast enhancement approaches, histogram modification based methods have received the greatest attention owing to their simplicity and effectiveness [1]. In particular, since global histogram equalization (GHE) tends to over-enhance the image details, the approaches of dividing an image histogram into several sub-intervals and modifying each sub-interval separately have been considered as an alternative to GHE [2], [3]. The effectiveness of these sub-histogram based methods is highly dependent on how the image histogram is divided. The state-of-the-art algorithm [2] models the image histogram using the Gaussian mixture model (GMM) and divides the histogram using the intersection points of the Gaussian components. The divided sub-histograms are then separately stretched using the estimated Gaussian parameters.

Recently, technical breakthroughs of the color image enhancement have been found using depth [4]–[6] or stereo [7]–[9] as side information. Stereo matching algorithms and depth sensors are now providing highly accurate depth images, and thus the use of the depth image for the color image enhancement becomes an important research issue. In this letter, we propose a new contrast enhancement algorithm that exploits the histograms of both color and depth images. To this end, the histograms of color and depth images are first divided into sub-intervals using the GMM. The intervals of the color image histogram are then adjusted such that the pixels with the similar intensity and depth values can belong to the same interval. The proposed algorithm is thus implicitly*depth adaptive*, and the experimental results demonstrate the effectiveness of the proposed algorithm.

The rest of the paper is organized as follows. In Section II, the proposed image contrast enhancement algorithm is described. Experimental results are presented in Section III, followed by the conclusion in Section IV.

II. Proposed Algorithm

We use a pair of color and depth images as input, as shown in Fig. 1. The proposed algorithm modifies the histogram of the color image using the histogram of the depth image as side information. When representing the histogram of the color image, we transform the color space from the RGB space to the hue-saturation-intensity (HSI) space and use only the intensity channel. Histogram modification is thus applied to the intensity channel, and the resultant color image is obtained by transforming the color space back to the RGB space. Figs. 2(a) and (b) show the histograms of the color and depth images with their estimated GMMs. The significant intersection points [2] (marked by the blue dots in Figs. 2(a) and (b)) are then used to divide the histogram into sub-intervals. Note that we adopt the GMM-based histogram partitioning method due to its effectiveness in the contrast enhancement [2], [11], but other histogram partitioning algorithms [3], [12] can also be worked with the proposed algorithm.

Let $\mathbf{c}$ and $\mathbf{d}$ represent the color image and the depth image, respectively. The histograms of $\mathbf{c}$ and $\mathbf{d}$ are assumed to be divided into N and M sub-intervals, respectively, and the intersection points between the i-th and $i+1$-th sub-intervals of $\mathbf{c}$ and $\mathbf{d}$

Manuscript received August 15, 2013; revised January 23, 2014; accepted January 24, 2014. Date of publication January 28, 2014; date of current version February 06, 2014. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Alexander C. Loui.

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Digital Object Identifier 10.1109/LSP.2014.2303157

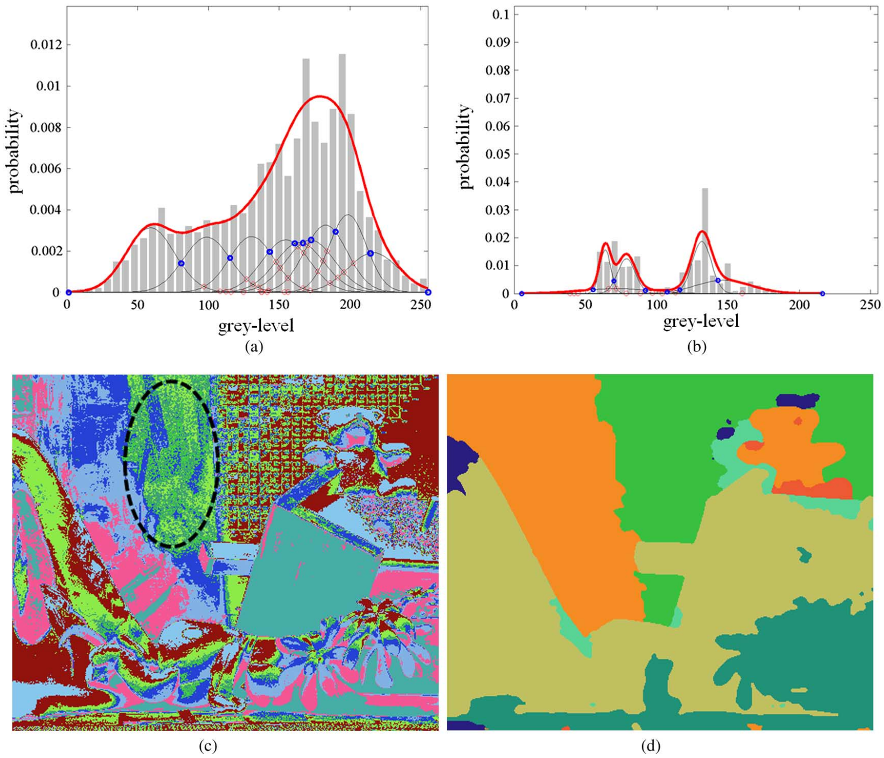

Fig. 2. (a)-(b) Histogram and layer partitioning results of Figs. 1(a) and (b), respectively. (c)-(d) Layer labeling results of Figs. 1(a) and (b), respectively.

are denoted as l_i^o and m_i^o, respectively. Using the intersection points, $\mathbf{c}$ and $\mathbf{d}$ can be decomposed into multiple layers as

$$S_{\mathbf{l}^o}(k) = \{(i,j) | l_{k-1}^o \leq \mathbf{c}(i,j) < l_k^o\}, k = 1, \ldots, N,$$
$$S_{\mathbf{m}^o}(k) = \{(i,j) | m_{k-1}^o \leq \mathbf{d}(i,j) < m_k^o\}, k = 1, \ldots, M. \quad (1)$$

where (i,j) represents a pixel coordinate, and $S_{\mathbf{l}^o}(k)$ and $S_{\mathbf{m}^o}(k)$ are the sets of pixels in the k-th layer of $\mathbf{c}$ and $\mathbf{d}$, respectively. l_0^o and l_N^o are the start and end positions corresponding to the first and last sub-intervals, respectively, and m_0^o and m_M^o are defined similarly. Figs. 2(c) and (d) show the layer labeling results for Fig. 1(a) and (b), respectively. Here, the pixels with the same color belong to the same layer. It should be noted that the adopted GMM technique [2] automatically determines the number of GMMs, and thus N and M are different for each color and depth image pair.

In histogram partitioning-based contrast enhancement algorithms, the mapping function for each layer is estimated exclusively such that image details in each layer can be effectively enhanced [2], [3]. However, histogram partitioning using only the intensity channel can assign different labels to the neighboring pixels that have similar intensity and depth values. For example, the background region inside the dotted circle in Fig. 2(c) has similar intensity and depth values as can be seen in Fig. 1, but different labels are cluttered in the region. Thus, the contrast enhancement on this background region using the conventional method [2] can yield unnatural images. To this end, we propose an algorithm that adjusts the histogram partitioning such that a same label is enforced for the pixels with the similar intensity and depth values.

Specifically, we modify the layer intersection positions of the color histogram as

$$\mathbf{l}^* = \arg\min_{\mathbf{l}} \{\varepsilon(\mathbf{l}; \mathbf{l^o}, \mathbf{m^o})\}, \quad (2)$$
$$\varepsilon(\mathbf{l}; \mathbf{l^o}, \mathbf{m^o}) = \|\mathbf{l} - \mathbf{l^o}\|^2 + \lambda d(S_{\mathbf{l}}, S_{\mathbf{m^o}}) \quad (3)$$

where $\|\cdot\|$ represents an Euclidean norm, λ is a weighting factor, $\mathbf{l}^* = \{l_1^*, \ldots l_{N-1}^*\}$, and $l_1^* \leq l_2^* \leq \ldots \leq l_{N-1}^*$. $\mathbf{l}$, $\mathbf{l}^o$, and $\mathbf{m}^o$ are defined in a similar manner. The first term in (3) is used to prevent an excessive change of the intersection positions, whereas the second term is used to measure the spatial dissimilarity between the layer labelings obtained using the current estimate $\mathbf{l}$ and the depth partitioning result $\mathbf{m}^o$, respectively. The dissimilarity function d is defined as (4), shown at the bottom of the page, where H and W represent the height and width of the image, respectively, $|S|$ denotes the cardinality

$$d(S_{\mathbf{l}}, S_{\mathbf{m}^o}) = \frac{H \times W}{\sum_{i=1}^{N-1} \{\max_k |S_{\mathbf{l}}(i) \cap S_{\mathbf{m}^o}(k)|\} + \sum_{i=1}^{M-1} \{\max_k |S_{\mathbf{m}^o}(i) \cap S_{\mathbf{l}}(k)|\}}, \quad (4)$$

of the set S, and $\cap$ is the set-intersection operator. When computing the denominator of (4), a maximally overlapping set in $S_{\mathbf{m}^o}$ is found for the i-th set $S_{\mathbf{l}}(i)$, and the size of overlapping is then accumulated for all color sets in $S_{\mathbf{l}}$. The similar procedure is performed for all depth sets in $S_{\mathbf{m}^o}$. Thus, the dissimilarity function d decreases as the amount of overlapping between $S_{\mathbf{l}}$ and $S_{\mathbf{m}^o}$ increases.

Note that we do not explicitly enforce that the spatially neighboring pixels with the similar color and depth values are grouped together since such an explicit enforcement requires a complicated pixel-level optimization. Instead, the color layer labeling is guided to be spatially overlapped with the depth layer labeling such that the neighboring pixels with the similar color and depth values are likely to be merged together. Our implicit enforcement thus yields a simple layer-level optimization.

By solving (2), modified histogram sub-intervals are obtained. Due to the non-differentiability of (4), we adopt the genetic algorithm (GA), which is a powerful tool for solving nonlinear and/or nonconvex functions. Although the global optimum is not guaranteed, we empirically found that the GA performs well when the initial color layer labeling $\mathbf{l}^o$ is used as the initial estimate of $\mathbf{l}$. The interested readers are referred to [13] for the details about implementation and parameter settings of the GA. Regarding the GA, only the difference compared to [13] is our use of (3) as a fitness function.

In (3), λ controls the amount of interval changes. If $\lambda = 0$, the original intervals remain, and thus the proposed method reduces to [2]. Otherwise, if λ increases, the dissimilarity term becomes dominant. The size of overlapping between $S_{\mathbf{l}}$ and $S_{\mathbf{m}^o}$ is maximized when $S_{\mathbf{l}}$ and $S_{\mathbf{m}^o}$ become equivalent. However, it needs to be noted that the order of pixel values should be maintained when a color image is divided into multiple layers [2], [3]. Therefore, in practice, we can only make $S_{\mathbf{l}}$ to be largely overlapped with $S_{\mathbf{m}^o}$.

Finally, using the modified histogram sub-intervals, a mapping curve of the color intensity is obtained using the method described in [2]. Note that our contribution is the modification method of the histogram sub-intervals, and thus a development of a new mapping-curve generation algorithm is out of focus in this letter.

III. Experimental Results

In order to evaluate the performance of the proposed algorithm, the Middlebury stereo test images [14] were used in our experiment. The depth images were obtained using the stereo matching algorithm [10] as shown in Fig. 3. The pixel values of the color images were then divided by 4 to simulate low-contrast input images. Using the same histogram partitioning and mapping curve generation methods in [2], the effectiveness of the proposed algorithm can be evaluated by comparing the results obtained with and without modifying the histogram sub-intervals, respectively. As discussed in Section II, the amount of modification in the histogram sub-intervals is dependent on λ. Fig. 4 shows that the layer labeling result $S_{\mathbf{l}^*}$ became more spatially uniform as λ increased. We empirically found that $\lambda = 1000$ performed well in enhancing the contrast of images. The results given hereafter were obtained using $\lambda = 1000$.

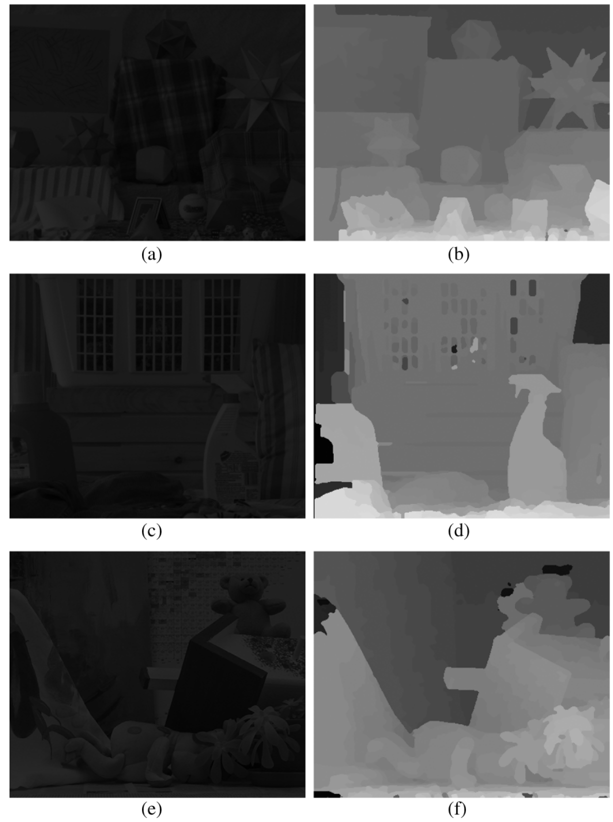

Fig. 3. Test color and depth image pairs. (a)-(b) $Moebius$ (463×370), (c)-(d) $Laundry$ (447×370), (e)-(f) $Teddy$ (450×375).

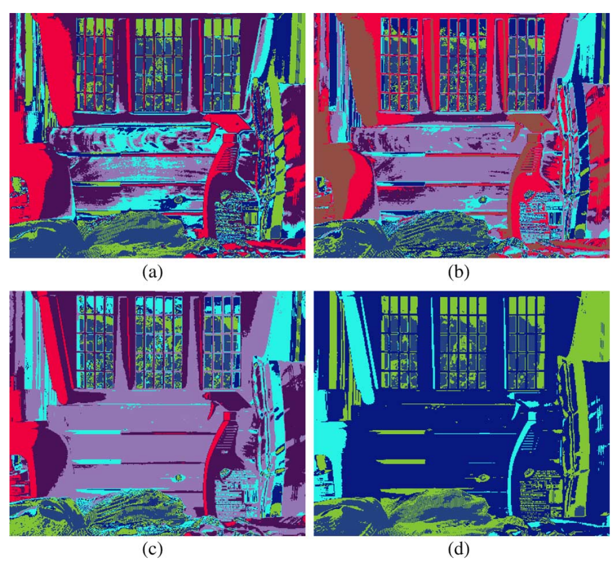

Fig. 4. Segmented image layers of $Laundry$ obtained by the proposed algorithm with (a) $\lambda = 10$, (b) $\lambda = 100$, (c) $\lambda = 1000$, (d) $\lambda = 10000$.

Fig. 5 shows the experimental results obtained using the conventional [2] and proposed algorithms. Both algorithms successfully enhanced the global contrast of the input images shown in Fig. 3. However, the conventional method produced artifacts at some image regions as shown in Figs. 5(g), (i), and (k). This is because the image regions with the similar intensity and depth values were decomposed into different groups as shown in Figs. 6(a), (c), and (e). By using the proposed algorithm, such regions were merged into the same layer as shown

Fig. 5. Experimental results corresponding to the input images in Fig. 3. (a)-(c) the resultant image obtained by [2], (d)-(f) the resultant image obtained by the proposed algorithm, (g), (i), (k): the magnified subregions corresponding to (a)-(c), respectively, (h), (j), (l) the magnified subregions corresponding to (d)-(f), respectively.

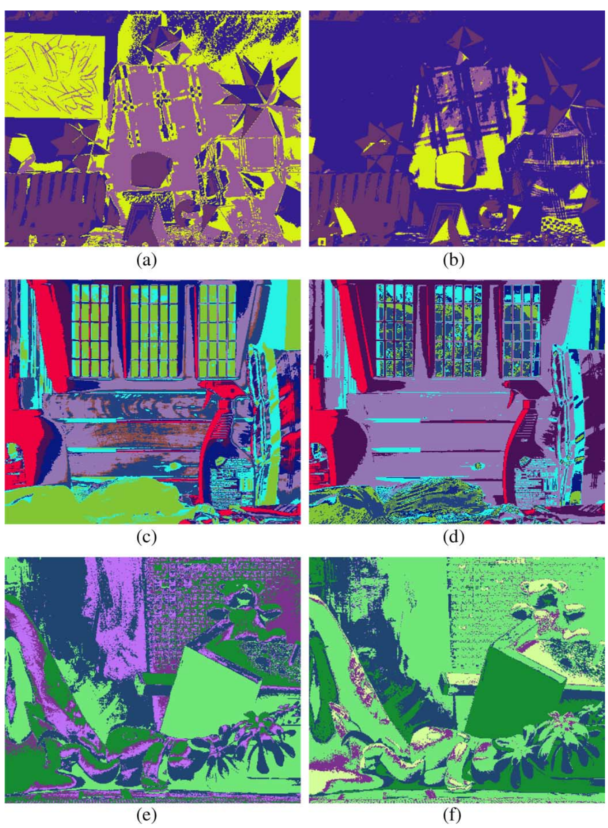

Fig. 6. Layer labeling results for the conventional method (first column) and the proposed method (second column).

in Figs. 6(b), (d), and (f), and thus the over-enhancement was prevented.

It should be noted that the depth image was used only for providing additional layer labeling information. Our layer-level optimization was not significantly dependent on pixel-level depth errors, and the use of the conventional stereo matching algorithm [10] was found to be effective. In our naive MATLAB implementation on a PC with 3Ghz CPU, 4 GB RAM, and Windows 7, it took about one minute to obtain a contrast-enhanced color image. About 20% of time was required for solving (2), and the other procedures including the GMM and mapping curve generation were more computationally demanding. It is expected that an efficient GPU implementation could significantly reduce the overall computational complexity.

IV. Conclusions

In this letter, we proposed a new histogram-based image contrast enhancement algorithm using the histograms of color and depth images. The histograms of the color and depth images are first partitioned into sub-intervals using the Gaussian mixture model. The partitioned histograms are then used to obtain the layer labeling results of the color and depth images. The sub-intervals of the color histogram are adjusted such that the pixels with the similar intensity and depth values can belong to the same layer. Therefore, while a global image contrast is stretched, a local image contrast is also consistently improved without the over-enhancement. We plan to extend our layer-based algorithm to a segment-based algorithm by using a joint color-depth segmentation method.

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