# Fast Depth Map Upsampling using Edge Information

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***Abstract*— In this paper, we propose a new depth map upsampling method to increase the depth image resolution using edge information. Although the joint bilateral upsampling (JBU) method expands the resolution of the depth map using two weighting functions, the complexity of JBU is relatively high. In the proposed upsampling method, we reduce the complexity of depth map upsmapling operation using a color weighting function chosen by the guide information. We use the modified mean absolute difference value with the Gaussian weighting function to obtain the guide information. Experimental results show that the proposed upsampler outperforms JBU in terms of the computational complexity.**

***Keywords—joint bilateral filter; depth map upsampling***

## I. Introduction

In the three-dimensional (3D) video applications, depth maps are used for synthesizing new images. Thus, accurate and high resolution depth sensing is a fundamental challenge in 3D video applications. Recently, Kinect depth camera and Time-of-Flight (ToF) range camera became a popular alternative for dense depth sensing. However, these methods provide low resolution and low frame rate depth video. For actual utilization, an efficient depth upsampling is necessary. Former image upsamplers, such as bilateral upsampler (BU), can be directly used own image for depth upsampling [1]. Such filtering techniques can often over smooth results, especially depth discontinuity regions. In order to increase the resolution and reduce depth image errors, Yang *et al.* applied bilateral filtering to a depth cost volume and a color image in an iterative refinement process [2]. Kopf et al. proposed joint bilateral upsampling (JBU) using the bilateral filter [3]. JBU removes the over smooth at the depth discontinuity region by adding additional information. The information is an original color image used in depth estimation. However, there are two problems on JBU: computational complexity and visual artifacts. Since JBU uses color data additionally, it cause much slower than other upsamplers.

In this paper, we propose a new depth image upsampler that uses depth edge information to decide the weighting functions in JBU. To reduce the computational complexity, we perfom edge detection using modified mean absolute difference before the JBU. Based on edge information, we can decide to use spatial weighting function or color weighting function, or both. In our experiments, the proposed upsampler makes high-resolution depth images fast while protecting edge information.

## II. Fast Depth Map Upsampling using Edge Information

A joint bilateral upsampling has two kernel which are spatial filter kernel and a range filter kernel for measuring the spatial and range distance between the center pixel and its neighbors, respectively. Assume that there are a low resolution depth image $D^l$, a high resolution depth image $D^h$ and high resolution color image $I^h$. Let $p$ and $q$ denote coordinates of pixels in $I^h$, and $p_\downarrow$ and $q_\downarrow$ denote the associated coordinates in $D^l$. The center pixel at a local window $W\times W$ is $p$. The neighboring pixel of $p$ at the window is $q$ where $q \in W\times W$. Formally, the depth value $D_p^h$ at $p$ in an upsampled depth image $D^h$ is computed by JBU as Eq. (1).

$$D_p^h = \frac{\sum_{q\in w\times w} \gamma_{p,q}\, D_q^l}{\sum_{q\in w\times w} \gamma_{p,q}}, \tag{1}$$

where $\gamma_{p,q}$ is a kernel weighting function.

$\gamma_{p,q}$ is defined by Eq. (2).

$$\gamma_{p,q} = \alpha(\| p_\downarrow - q_\downarrow \|)\cdot \beta(\| I_p^h - I_q^h \|), \tag{2}$$

where $\alpha$ and $\beta$ are spatial and the color weighting functions, respectively, and $\|\cdot\|$ is an Euclidean distance operator. If we modeling α and β using an exponential function, those weighting functions are represented by Eq. (3).

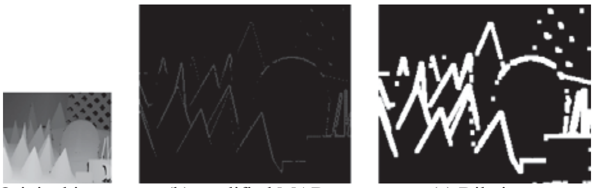
$$\alpha(x) = \exp\left(\frac{-x^2}{\sigma_\alpha}\right),\ \ \beta(x) = \exp\left(\frac{-x^2}{\sigma_\beta}\right). \tag{3}$$

The smoothing parameters of α and β are can be represented by $\sigma_\alpha$ and $\sigma_\beta$.

In our algorithm, we use the modified mean absolute difference (modified MAD) value to get the edge information. According to the differences between center pixel and neighbor pixels, we can get the edge information. Assume that M is the result of the modified MAD. M is represented by Eq. (4).

$$\mathrm{M} = \frac{1}{k} \sum_{n \in W \times W} G_\sigma(||p - q_n||)|p - q_n| \quad (4)$$

where $G_\sigma$ is gaussian function for more weighting near center pixels, and k is the number of pixels in window. Also, we apply the MAD calculation using the cross-shaped window to reduce the complexity.



(a) Original image (b) modified MAD (c) Dilation

Fig. 1. Result of the modified MAD

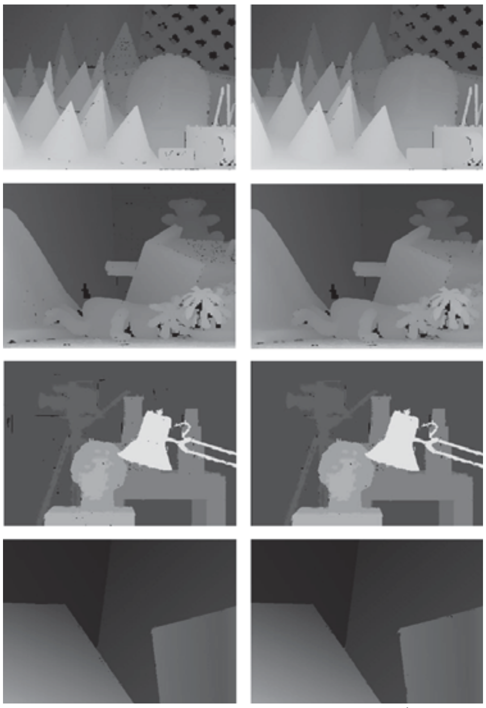
According to the edge information, we choose different weighting functions for depth map upsampling. For the edge pixels, we use spatial and color weighting functions like JBU. Otherwise, we use only spatial weighting functions as Eq. (5).

$$\gamma_{p,q} = \alpha(\| p_\downarrow - q_\downarrow \|). \quad (5)$$

The only difference to between Eq. (2) and Eq. (5) is that the color weighting functions are not used.

## III. Experimental Results

In our experiment, we have used four test image sets Cones, Teddy, Tsukuba and Venus provided by the Middlebury Stereo were used [4]. The ground-truth depth images were downsampled by factors of 2, 4 and 8 using the nearest neighbor method.



JBU Proposed

Fig. 2. Upsampled depth maps

The proposed methods is compared with the JBU. Fig 2 shows the upsampled depth maps of scaling factor 4.

TABLE I. Performance Comparison

| Scaling factor | Image | BPR (%) | | TIME (sec.) | |
|---|---|---|---|---|---|
| | | JBU | Proposed | JBU | Proposed |
| 2 | Cones | 2.41 | 2.40 | 2.89 | 2.13 |
| | Teddy | 4.62 | 4.62 | 2.76 | 2.16 |
| | Tsukuba | 3.12 | 3.09 | 1.82 | 1.18 |
| | Venus | 0.21 | 0.21 | 2.80 | 1.95 |
| 4 | Cones | 4.31 | 4.29 | 7.72 | 2.35 |
| | Teddy | 6.91 | 6.90 | 7.62 | 2.37 |
| | Tsukuba | 6.82 | 6.82 | 5.02 | 1.42 |
| | Venus | 0.10 | 0.99 | 7.56 | 2.24 |
| 8 | Cones | 10.03 | 10.01 | 12.07 | 2.63 |
| | Teddy | 11.02 | 11.01 | 11.51 | 2.62 |
| | Tsukuba | 8.84 | 8.84 | 7.67 | 1.74 |
| | Venus | 3.81 | 3.42 | 11.12 | 2.59 |

Table 1 shows bad pixel rate (BPR), that was calculated with respect to the ground-truth depth images. We can find that BPR of joint bilateral upsampler and proposed method are almost same. Table 1 also shows the processing time consumption comparison with JBU. We can find that our method is much faster than JBU. Therefore, the proposed method has better performance than JBU in computational complexity.

## IV. Conclusion

In this paper, we proposed a depth image upsampling method using the depth edge information and JBU. In comparison to JBU, this method accelerates the overall upsampling process. Test results confirmed that the proposed method shortened the processing speed by 59% on average compared to that of JBU despite inducing almost same quality.

## V. Acknowledgment

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## VI. References

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