HIGH RESOLUTION DEPTH IMAGE RECOVERY ALGORITHM USING GRAYSCALE IMAGE

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ABSTRACT

This paper proposes a depth image recovery algorithm which recovers depth images using grayscale images and low resolution depth images. Based on a image colorization technique, a depth value image recovery problem is formulated as a convex quadratic optimization problem, and a fast depth image recovery algorithm is proposed. Experimental results show that the proposed algorithm recovers a high resolution depth image from a very low resolution depth image effectively.

***Index Terms*—** depth image recovery, image colorization, depth sensor

1. INTRODUCTION

The development of depth sensors such as Microsoft Kinect enables us to capture depth images in real-time and with low cost, which leads various researches [1, 2], e.g., 3D reconstruction, segmentation, recognition, tracking, etc. Recently, some smartphone have a depth sensor, which provides some useful features such as refocusing to let owners change what appears in focus in photos after they are taken. It can be expected that some smartphone will have depth sensors and that a lot of applications will be developed using depth sensors. However, a depth sensor on a smart phone captures a very low resolution depth image due to the limitations of hardware and cost. Therefore recovering a high resolution depth image from low resolution images is important to provide the applications which are developed for PCs using a high resolution depth sensor such as Microsoft Kinect. Because most smartphone have a high resolution RGB camera, this paper focuses on improvement of resolution of a depth sensor using an RGB camera. The objective of this paper is to propose a high resolution depth image recovery algorithm from a very low resolution depth image using a grayscale image.

Several works have proposed depth image recovery algorithms using a given low resolution depth image and an RGB image [3–7], and most of them are based on the traditional image processing technique. In [4] depth image recovery method is proposed based on the autoregressive (AR) model identified from an RGB image, and [5] uses an image segmentation technique to recover a depth image. A total generalized variation minimization based algorithm is proposed in [7] to obtain a high resolution depth image. While these algorithms recover depth images from low resolution images, they do not work well when a very low resolution depth image is given.

In order to recover high resolution depth images using a little depth information, this paper focuses on image colorization techniques [8, 9], which recover a full color image from a grayscale image using a small number of pixels with color information. We make some assumptions of the relationship between a grayscale image and a depth image, and a depth image recovery problem is formulated as a convex quadratic programming similar to the colorization algorithm proposed in [9]. Experimental results show that the proposed algorithm recovers a high resolution depth image effectively. The contribution of this paper is to provide a simple algorithm to obtain a high resolution depth image from a very low resolution image based on the image colorization algorithm.

2. MAIN RESULTS

This paper considers a problem of recovering a high resolution depth image using a low resolution depth image and a high resolution grayscale image. Let $\boldsymbol{x} \in \boldsymbol{R}^{mn}$ and $\boldsymbol{v} \in \boldsymbol{R}^{mn}$ denote high resolution depth and grayscale images. Then the recovery problem considered in this paper is to find $\boldsymbol{x}$ using the value of $\boldsymbol{v}$ and x_i for $i \in \mathcal{I}$, where $\mathcal{I}$ denotes a given set of vector indices corresponding to depth values given from a low resolution image.

First, let us consider a recovery problem only using the knowledge of a low resolution depth image. We make a natural assumption that the differences of depth values between the neighbor pixels are small and then formulate the depth image recovery problem as follows,

$$\begin{array}{ll} \text{Minimize} & \|D\boldsymbol{x}\|_2^2 \\ \text{subject to} & (\boldsymbol{x})_i = d_i, \forall i \in \mathcal{I}, \end{array} \quad (1)$$

where d_i is obtained from a low resolution depth image, and $(\cdot)_i$ denotes the ith element of a vector. The matrix $D \in$

$\boldsymbol{R}^{(2mn-m-n)\times mn}$ is the difference operator defined by

$$D = [U^T \ V^T]^T,$$

where $U \in \boldsymbol{R}^{(m-1)\times m}$ and $V \in \boldsymbol{R}^{m(n-1)\times mn}$ denote vertical and horizontal difference operator matrices whose (i,j)-element $(U)_{i,j}$ and $(V)_{i,j}$ are given by

$$(U)_{i,j} = \begin{cases} 1, & \text{if } i = j \\ -1, & \text{if } i+1 = j \\ 0, & \text{otherwise} \end{cases}$$

and

$$(V)_{i,j} = \begin{cases} 1, & \text{if } i = j \\ -1, & \text{if } i+M = j \\ 0, & \text{otherwise} \end{cases},$$

respectively. This problem recovers depth values by spreading the depth information like the colorization algorithm proposed in [8]. However, numerical experiments indicate that this problem does not recover the depth image well when depth values of only a few pixels are known, that is, a very low resolution depth image is given. Hence similar to the colorization algorithm proposed in [9], this paper makes an additional assumption that the differences of depth values between neighbor pixels can be modeled using a vector function $\boldsymbol{f}$ of a grayscale image described by

$$D\boldsymbol{x} = \alpha \boldsymbol{f}(\boldsymbol{v}), \tag{2}$$

where α is an unknown positive constant. This paper proposes the function $\boldsymbol{f}$ satisfying the following equation,

$$|(\boldsymbol{f}(\boldsymbol{v}))_i| = |(D\boldsymbol{v})_i|. \tag{3}$$

This implies that depth values change smoothly in the smooth region of the grayscale image and significantly in the edge region. From (2) and (3) we have that

$$|(D\boldsymbol{x})_i| = \alpha |(D\boldsymbol{v})_i|. \tag{4}$$

Then this paper provides the following depth value recovery problem by appending the above constraints to (1),

$$\begin{array}{ll} \text{Minimize} & \|D\boldsymbol{x}\|_2^2 \\ \text{subject to} & (\boldsymbol{x})_i = d_i, \ \forall i \in \mathcal{I} \\ & |(D\boldsymbol{x})_i| = \alpha |(D\boldsymbol{v})_i| \end{array}, \tag{5}$$

where $\boldsymbol{x}$ and α are design variables.

Next we focus on eliminating the unknown constant α from (5). It holds from (4) that

$$\|D\boldsymbol{x}\|_2^2 = \alpha^2 \sum_{i=1}^{2mn-m-n} |(D\boldsymbol{v})_i|^2.$$

Since $(D\boldsymbol{v})_i$ is a constant, (5) can be described as follows,

$$\begin{array}{ll} \text{Minimize} & \alpha^2 \\ \text{subject to} & (\boldsymbol{x})_i = d_i, \ \forall i \in \mathcal{I} \\ & |(D\boldsymbol{x})_i| = \alpha |(D\boldsymbol{v})_i| \end{array}.$$

Because it holds that $\alpha = |(D\boldsymbol{x})_i|/|(D\boldsymbol{v})_i|$ under the assumption $|(D\boldsymbol{v})_i| \neq 0$, we have that

$$\alpha^2 = \sum_{i=1}^{2mn-m-n} \left(\frac{(D\boldsymbol{x})_i}{(D\boldsymbol{v})_i} \right)^2.$$

Hence (4) is equal to the following problem,

$$\begin{array}{ll} \text{Minimize} & \|FD\boldsymbol{x}\|_2^2 \\ \text{subject to} & (\boldsymbol{x})_i = d_i, \ \forall i \in \mathcal{I} \end{array}, \tag{6}$$

where F is a diagonal matrix whose diagonal elements $(F)_{ii}$ are defined by $(F)_{ii} = 1/|(D\boldsymbol{v})_i|$. Since the value of $|(D\boldsymbol{v})_i|$ may practically take 0, we use F given by

$$(F)_{ii} = \frac{1}{|(D\boldsymbol{v})_i| + \varepsilon}, \tag{7}$$

where $\varepsilon > 0$ is a small constant to avoid zero divide.

While the problem (6) is a convex optimization and can be solved exactly, this paper proposes the following Lagrangian relaxation problem to provide a fast algorithm,

$$\text{Minimize} \quad \|FD\boldsymbol{x}\|_2^2 + \lambda_1 \|M(\boldsymbol{x} - \boldsymbol{d})\|_2^2, \tag{8}$$

where $\lambda_1 > 0$ is a given constant, $\boldsymbol{d}$ is a vector whose ith element is equal to d_i for $i \in \mathcal{I}$, and M is a diagonal matrix whose diagonal element is defined by

$$M_{i,i} = \begin{cases} 1 & \text{if } i \in \mathcal{I} \\ 0 & \text{otherwise} \end{cases}.$$

Since (8) is a least squares problem, its solution is obtained as

$$\boldsymbol{x} = \begin{bmatrix} FD \\ \lambda_1 M \end{bmatrix}^{\dagger} \begin{bmatrix} \boldsymbol{0} \\ \lambda_1 M\boldsymbol{d} \end{bmatrix}, \tag{9}$$

where $\boldsymbol{0}$ denote the zero vector of size $2mn - m - n$, and $A^{\dagger}$ denotes the pseudoinverse of a matrix A.

If the grayscale image and the depth image satisfy the assumption (3), (9) achieves a high performance. However, most grayscale images do not satisfy this assumption, e.g. they have discoloration in smooth depth region, that is, differences between neighbor pixels of the grayscale image may be large even when corresponding differences of the depth image are smooth due to image textures, patterns and so on. In order to decrease the effect of these noises, this paper proposes to modify the given grayscale image using a depth image. Let $\boldsymbol{d}^* \in \boldsymbol{R}^{mn}$ denotes the depth image recovered in (9). Then, similar to (5), this paper proposes the following problem,

$$\begin{array}{ll} \text{Minimize} & \|D\boldsymbol{v}^*\|_2^2 + \lambda_2 \|\boldsymbol{v}^* - \boldsymbol{v}\|_2^2 \\ \text{subject to} & |(D\boldsymbol{v}^*)_i| = \beta |(D\boldsymbol{d}^*)_i| \end{array}, \tag{10}$$

where the $\lambda_2 > 0$ is a given constant, and β is an unknown positive constant. Then (10) is reformulated as follows in the same way to provide (6) from (5),

$$\text{Minimize} \quad \|GD\boldsymbol{v}^*\|_2^2 + \lambda_2 \|\boldsymbol{v}^* - \boldsymbol{v}\|_2^2, \tag{11}$$

Algorithm 1 High resolution depth image recovery algorithm.

Require: $\boldsymbol{v}$, ε, λ_1, λ_2, $\mathcal{I}$ d_i for $i \in \mathcal{I}$ and T

set $t \leftarrow 1$

set $(F)_{ii} = \frac{1}{|(D\boldsymbol{v})_i|+\varepsilon}$ for $i = 1, 2, \ldots, 2mn - m - n$.

$$\boldsymbol{d}^* \leftarrow \begin{bmatrix} FD \\ \lambda_1 M \end{bmatrix}^\dagger \begin{bmatrix} \mathbf{0} \\ \lambda_1 M\boldsymbol{d} \end{bmatrix}$$

repeat

update $(G)_{ii} = \frac{1}{|(D\boldsymbol{d}^*)_i|+\varepsilon}$ for $i = 1, 2, \ldots, 2mn - m - n$.

$$\boldsymbol{v}^* \leftarrow \begin{bmatrix} GD \\ \lambda_2 E \end{bmatrix}^\dagger \begin{bmatrix} \mathbf{0} \\ \lambda_2 \boldsymbol{v} \end{bmatrix}$$

update $(F)_{ii} = \frac{1}{|(D\boldsymbol{v}^*)_i|+\varepsilon}$ for $i = 1, 2, \ldots, 2mn - m - n$.

$$\boldsymbol{d}^* \leftarrow \begin{bmatrix} FD \\ \lambda_1 M \end{bmatrix}^\dagger \begin{bmatrix} \mathbf{0} \\ \lambda_1 M\boldsymbol{d} \end{bmatrix}$$

$t \leftarrow t + 1$

until $t = T$

Ensure: $\boldsymbol{d}^*$

where diagonal matrix G is given by

$$(G)_{ii} = \frac{1}{|(D\boldsymbol{d}^*)_i| + \varepsilon}. \tag{12}$$

The least squares solution of (11) can be obtained simply as

$$\boldsymbol{v}^* = \begin{bmatrix} GD \\ \lambda_2 E \end{bmatrix}^\dagger \begin{bmatrix} \mathbf{0} \\ \lambda_2 \boldsymbol{v} \end{bmatrix}, \tag{13}$$

where $\boldsymbol{E} \in \boldsymbol{R}^{mn\times mn}$ denotes the identity matrix. After calculating (13), we re-generate F in (7) using $\boldsymbol{v}^*$, and a depth image is recovered again. This paper proposes to recover iteratively depth image and grayscale image, and the proposed depth image recovery algorithm is shown in Algorithm 1, where the iteration is repeated T times.

3. EXPERIMENTAL RESULTS

This section provides the experimental results to show the effectiveness of the proposed algorithm comparing with the algorithm proposed in [7] (we use the source code available at the website[1]) using the grayscale and depth images from the Middlebury datasets as shown in Fig. 1. In all experiments we use $\varepsilon = 10^{-3}$, $\lambda_1 = 10^8$, $\lambda_2 = 10^{-5}$ and $T = 3$ in Algorithm 1, and the parameters of the algorithm proposed in [7] are used as $\alpha_0 = 0.267, \alpha_1 = 0.03$, which are also used in numerical experiments of [7]. We recover 1088×1376 depth images using the same size grayscale images and low resolution depth images of size 34×43 or 17×22 pixels as shown in Fig. 2. The depth values of given low resolution depth image are projected on grid points of high resolution depth image to be recovered, and these points are in center of the each corresponding range as shown in Fig. 3.

Fig. 1. Test images (1088 × 1376): (a) art grayscale image, (b) art depth image, (c) books grayscale image, (d) books depth image, (e) moebius grayscale image and (f) moebius depth image.

The results are shown in Table 1, Table 2, Fig. 4 and Fig. 5. Table 1 and 2 show the root of the mean square error (RMSE) of recovered depth images calculated by

$$RMSE = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(X_{i,j} - X^*_{i,j})^2}, \tag{14}$$

where $X \in \boldsymbol{R}^{mn}$ and $X^* \in \boldsymbol{R}^{mn}$ denote the original and recovered depth images, respectively. We can see that the proposed algorithm achieves the high recovery performance better than the algorithm proposed in [7]. The resulting depth images of test images are shown in Fig. 4 and Fig. 5. As can be seen, the proposed algorithm can recover the depth image from a few depth values.

[1] http://rvlab.icg.tugraz.at/project_page/project_tofusion/project_tofsuperresolution.html

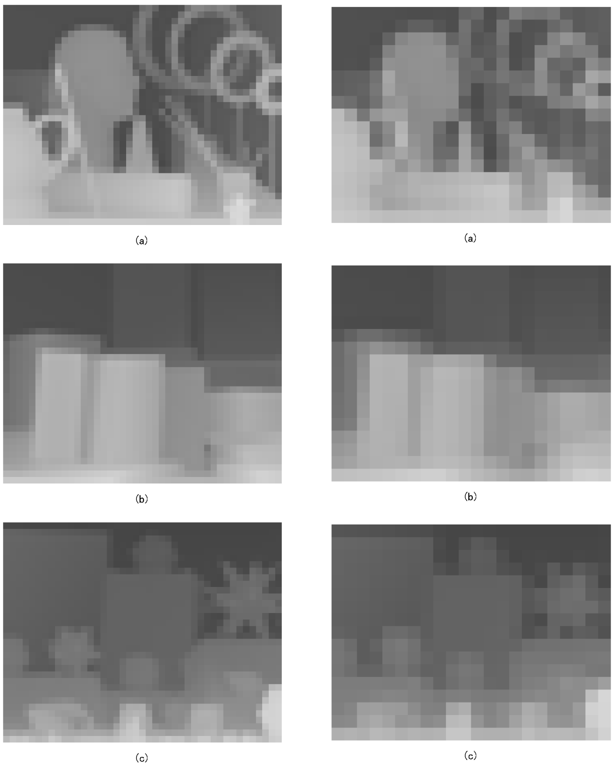

Fig. 2. Given depth images : (a), (b) art depth image, (c), (d) books depth image, (e), (f) moebius depth image, and the image sizes of left column is 34 $\times$ 43 and right column is 17 $\times$ 22, respectively.

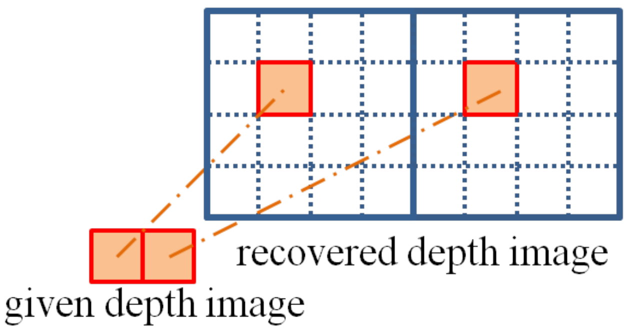

Fig. 3. Projection from a low resolution depth image to a recovered depth image.

4. CONCLUSION

This paper proposes a depth image recovery algorithm using a grayscale image and a very low resolution depth image. In order to achieve good recovery, we make an assumption about the relationship between grayscale images and depth images, and the depth recovery algorithm is provided based on the colorization technique proposed in [9]. Because most images do not satisfy this assumption exactly, the proposed algorithm optimizes the given grayscale image using the depth image to improve a quality of high resolution depth image recovery. Experimental results show that the proposed algorithm can recover the depth images effectively from very low resolution images.

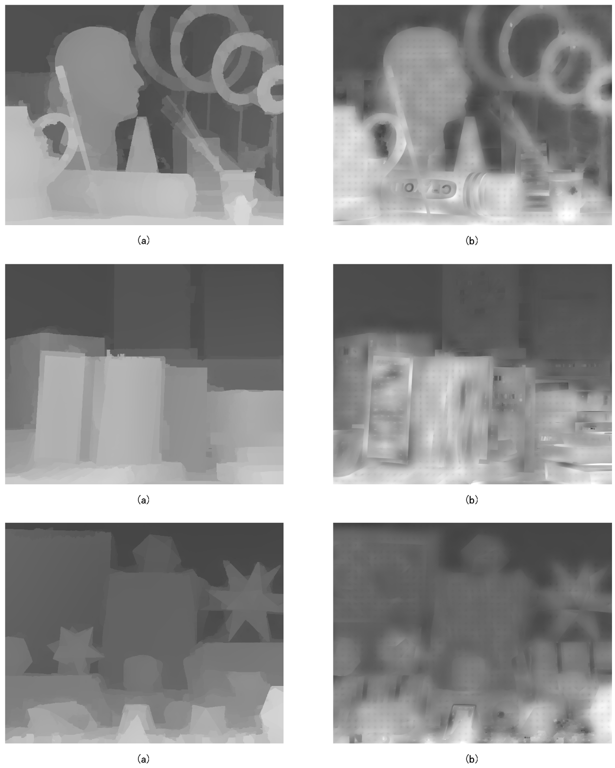

Fig. 4. Recovered depth images from 34 $\times$ 43 size images: (a), (c), (e) proposed algorithm and (b), (d), (f) algorithm proposed in [7], respectively.

Table 1. RMSE resulting from 34 $\times$ 43 size images

	art	books	moebius
proposed algorithm	**10.3637**	**4.3072**	**4.6311**
algorithm proposed in [7]	17.4189	12.9187	11.2142

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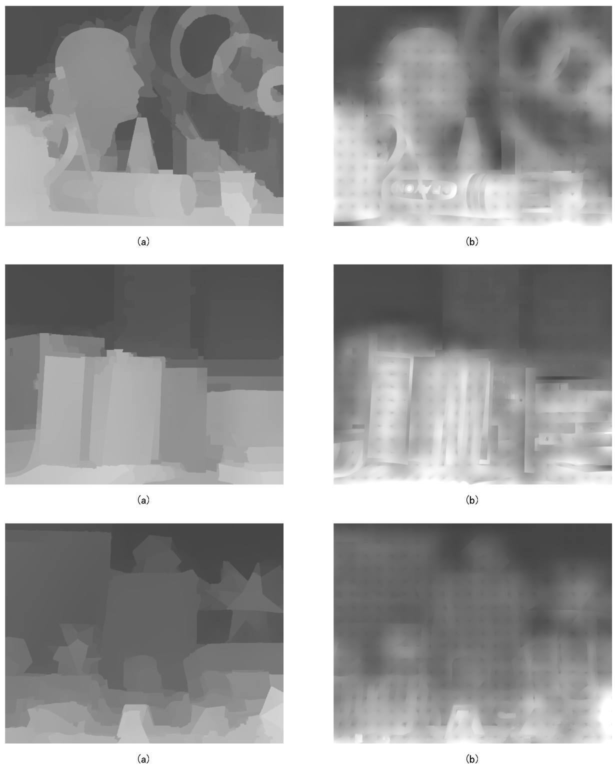

Fig. 5. Recovered depth images from 17 $\times$ 22 size images: (a), (c), (e) proposed algorithm and (b), (d), (f) algorithm proposed in [7], respectively.

Table 2. RMSE resulting from 17 $\times$ 22 size images

	art	books	moebius
proposed algorithm	**15.1839**	**7.3518**	**7.6603**
algorithm proposed in [7]	26.4142	21.5558	18.0470

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