Research on Super-resolution Reconstruction Method of Lidar 3D Range Profile

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Abstract： At present, how to use low-cost and superior algorithms to obtain high-resolution 3D range image is the focus of lidar research. In this letter, the low-resolution Gm-APD lidar is combined with the high-resolution ICCD lidar to obtain the registered low-resolution range image and high-resolution intensity image. This letter proposes an improved image guidance algorithm. The algorithm uses a Markov random field model to define a global energy function. This function combines the distance fidelity term and the regularization term to obtain a high-resolution 3D range image by solving the optimization model. The experimental results show that compared with the traditional algorithms, the algorithm improves the resolution of the range images, the edge of the reconstructed image is sharper than the regional similarity guidance algorithm, and the image quality evaluation index has the better value.

Key words：Super-resolution Reconstruction；laser radar；3D range image；ICCD

0 Introduction

In order to detect the real world, it is of great significance to extend the traditional two-dimensional imaging to a three-dimensional image with distance information. Three-dimensional imaging methods include stereo vision, stereo structured light, depth measurement cameras, scanning lidar, solid-state lidar, flash lidar, etc. [1], where lidar has unparalleled innate advantages: small size, light weight, and density of collected data It has the characteristics of large, high ranging accuracy, fast imaging speed, strong vegetation penetration, not affected by the solar altitude and shadow, good concealment, and strong anti-interference ability [2]. Based on these advantages, lidar 3D images are widely used in target detection, attitude recognition, survey monitoring, modeling and mapping, automatic navigation, 3D measurement, tracking guidance, etc. [3,4].

According to different detection forms, laser 3D imaging radar can be divided into scanning laser 3D imaging radar [5] and non-scanning laser 3D imaging radar [6]. In this paper, the Gm-APD (based on Geiger mode APD array) lidar is used for imaging to obtain the low-resolution three-dimensional range profile. The lidar belongs to the non-scanning laser three-dimensional imaging radar. It is easy to integrate, has high detection sensitivity, and has single photon detection ability. It only needs to emit a laser pulse once. The flight time of the pulse is measured by the detector, and the distance value of each pixel is calculated Therefore, it has more advantages in detecting weak signals, i.e. long-distance targets [7,8]. At present, the Lincoln Laboratory of Massachusetts Institute of technology is in the leading position in the research of this kind of lidar, and the number of Gm-APD lidar pixels can reach 256 × 256[9]. Domestic research started late in this field, and it limited by devices, the number of pixels (64 × 64). If we want to obtain high resolution 3D range profile from the hardware point of view, we need a large array of Gm-APD lidar, which is expensive. The super-resolution 3D reconstruction of ICCD lidar with high spatial resolution and Gm-APD lidar with high range resolution is a feasible technical way to obtain high spatial resolution 3D laser range profile. This method can effectively solve the problem of low resolution of lidar 3D range profile with low cost.

Image guided super-resolution range image reconstruction algorithm uses the intensity image collected by high-resolution sensor as prior knowledge to guide the reconstruction of low-resolution range image. This kind of image guided algorithm can be divided into two categories, one is the joint local linear filtering algorithm, the other is the global energy optimization algorithm based on Bayesian decision theory. The first is to introduce high-resolution image information on the basis of traditional bilateral filtering. Kopf et al. [10] proposed a joint bilateral up sampling filter (IBUF) method, in which high-resolution intensity image and distance image are regarded as two Gaussian kernels of the filter. JBUF is superior to the nearest neighbor interpolation, bicubic interpolation and Gaussian filter up-sampling algorithms in detail richness, edge sharpness and image quality evaluation index MSE. He et al. [11] proposed a local linear guided filter, which does not need to set the filter window size, and its running time is about one tenth of that of JBUF.

Based on the global energy optimization super-resolution reconstruction method, Diebel et al. [12] transformed the super-resolution reconstruction problem into solving the problem based on Markov random field optimization model. For the first time, the prior knowledge of color image was added to the regularization term, and the L2 norm models of distance fidelity term and regularization term were constructed. Park et al. [13] added the nonlocal mean term to the regularization term, and added the color similarity guidance term, super-pixel segmentation guidance term, edge saliency guidance term and bicubic interpolation guidance term to the smoothing term of the weighting function, and reconstructed the high-resolution image by solving the optimization function. The new model can obtain better details and edge structure, but more constraints increase the running time of the algorithm. Ferstl et al. [14] proposed a method based on anisotropic second-order generalized total variation (TGV) to calculate anisotropic diffusion tensor in color image to guide depth image super-resolution reconstruction. Lei et al. [15] added region similarity to the regularization term guided by color similarity and bicubic interpolation image to guide the generation of high-resolution range profile. Compared with other image guidance methods, this method runs faster and has better reconstruction effect. However, the standard deviation of the region similarity guidance term is fixed. For different distance images, region similarity over guidance or under guidance may occur As a result, the quality of reconstruction is not stable, and the image edge is blurred due to the transition point in the region with abrupt change in distance.

In this paper, based on the region similarity guidance algorithm proposed by Lei et al. Is improved. Aiming at the uncontrollable standard deviation of the region similarity guide term, the region similarity guidance term of the controllable Gaussian kernel function is proposed. For the edge ambiguity of the reconstructed image, the adaptive standard deviation of the Gaussian kernel function, the construction of the norm model based on local content perception, and the high score based on the partition interpolation are proposed. The range image and intensity image are obtained by using the dual sensor imaging system composed of Gm-APD lidar and ICCD lidar. The range image and intensity image are preprocessed and registered, and the improved image guidance algorithm is used for super-resolution reconstruction to obtain super-resolution three-Dimensional distance profile.

1 Imaging system and Theory of algorithm

1.1 Imaging system

The schematic diagram of dual wavelength laser composite imaging system is shown in Fig. 1. The optical imaging system is designed to simultaneously acquire the 3D range profile of low-resolution GM APD lidar and the intensity image of high resolution ICCD lidar, and perform super-resolution reconstruction of 3D range images. Image processing is divided into three steps: 1) preprocessing range image and intensity image; 2) registration of low-resolution range image and high-resolution intensity image; 3) super-resolution reconstruction of range image guided by high-resolution intensity image.

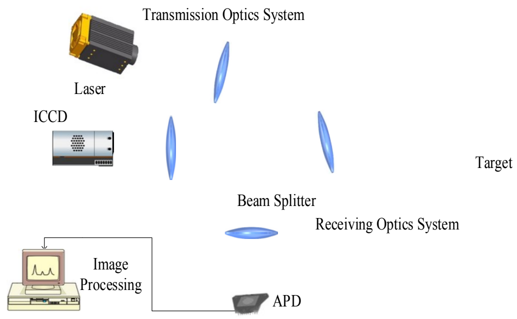


Fig 1 System schematic diagram

1.2 Brief Description of region similarity guided algorithm[15]

For the image defined in two-dimensional space, it can be regarded as a two-dimensional random field, and the Markov property describes the relationship between adjacent pixels in the image. Therefore, the digital image can be simulated by using Markov random field, and the super-resolution reconstruction problem is transformed into solving the optimization model of Markov random field. The key to solve this problem is to obtain the reconstruction distance which maximizes the posterior probability of Markov random field under the constraints of high-resolution intensity image Z and low-resolution range profile X. The probability distribution of Markov random field can be expressed by Gibbs distribution. The constraint term of posterior probability consists of two parts: the distance fidelity term P_d and the regularization term P_r. The conditional distribution of reconstruction distance y is expressed by the following formula:

$$P(y \mid x, z) = \frac{1}{E}\exp(-\frac{1}{2}(P_d + \lambda P_r)) \tag{1}$$

Where, λ is the weight of the range smoothing item, and E is the normalization factor. Therefore, the maximization of a posteriori probability distribution problem can be converted to a global energy minimization problem with respect to y:

$$y = \arg\min_{y}\{P_d + \lambda P_r\} \tag{2}$$

Energy optimization function:

$$E(D) = E_d(D) + \lambda E_r(D) \tag{3}$$

The energy optimization equation consists of a distance fidelity term and regularization term. Where D denotes the restored super resolution range image. The distance fidelity term is as follow:

$$E_d(D) = \sum_{p \in M} \left| D(p) - G(p) \right|^2 \tag{4}$$

The distance fidelity term describes the squared error of the distance map and the original low-resolution range map. It makes the restored high-resolution image not deviate from the low-resolution image too much. Where, G denotes the high-resolution range image obtained by interpolation of low-resolution range image, p is the pixel index, $M$is the set of measured range pixels, $|\cdot|$ denotes absolute value.

The regularization term describes a prior regularization of the estimated range map. It generates more reliable high-resolution images by introducing prior knowledge. The regularization term is as follow:

$$\begin{aligned} E_r(D) &= \sum_{\mathrm{p}} \sum_{q \in N(p)} \frac{w_{pq}}{W_p} \left| D(p) - D(q) \right|^2 \\ W_p &= \sum_q w_{pq} \end{aligned} \tag{5}$$

Where, p and q is the pixel index, $N(p)$ is the neighborhood set of p, W_p is a normalization factor, w_{pq} is the confidence weighting, computed by equation (6).

$$\begin{aligned} w_{pq} &= w_c \cdot w_g \cdot w_n \\ w_c &= \exp\left(-\frac{(I(p) - I(q))^2}{2\sigma_c^2}\right) \\ w_g &= \exp\left(-\frac{(D_g(p) - D_g(q))^2}{2\sigma_g^2}\right) \\ w_n &= \sum_{m \in \Omega(p)} h(m) \exp\left(-(D_g(p+m) - D_g(q+m))^2\right) \end{aligned} \tag{6}$$

Where, I denote the high-resolution intensity image, w_c represent the color similarity, it uses the texture edge information of high-resolution intensity image to guide the generation of new pixels; w_g introduce the guided bicubic interpolated range map, it is used to balance the guiding intensity of color similarity and reduce the occurrence of texture duplication; w_n are expressed by the patch similarity measure, designed by nonlocal mean filter, it can sharpen the edge, reduce the noise and protect the edge structure. σ_c and σ_g control the relative sensitivity of w_c and w_g, $m \in \Omega$ represents the vectors pointing to pixel p in local neighborhood window Ω, $h(m)$ is a Gaussian cornel weights. D_g represents the high-resolution range guidance image generated by bicubic interpolation of low-resolution range image.

1.3 Principle of improved algorithm

1) Region similarity guide term of controllable Gaussian kernel function

There is no standard deviation of Gaussian kernel function with adjustable sensitivity in the region similarity guidance term of regional similarity guidance algorithm. Therefore, in this paper, the standard deviation σ_n of controllable Gaussian kernel function is introduced into the region similarity guidance term w_n to adjust its sensitivity and facilitate the control of guidance intensity. The formula is as follows:

$$w_n = \sum_{m \in \Omega(p)} h(m) \exp\left(-\frac{(D_g(p+m) - D_g(q+m))^2}{2\sigma_n^2}\right) \tag{7}$$

2) Super pixel segmentation edge penalty guide term

The idea of edge penalty guidance for super-pixel segmentation comes from the super-resolution reconstruction algorithm proposed by Park et al. The simple linear iterative clustering (SLIC) method is used to segment the hyper pixel of high-resolution intensity image I. the image blocks with similar texture and intensity will be divided into the same label range. The weaker edge is not given weight penalty, while the stronger edge is given appropriate weight penalty to sharpen the edge. The super pixel segmentation edge penalty guide term w_s can be expressed as follows:

$$w_s = \left\{\begin{matrix} 1 & s(p) = s(q) \\ t_p & s(p) \neq s(q) \end{matrix}\right\} \tag{8}$$

Where, $s(\cdot)$ denotes super pixel segmentation mark serial number, t_p represents the weight of penalty，could be 0~1。

3) Construct L_α(α=1 or α=2) norm model based on local content perception

The distance fidelity term and regularization term of region similarity guidance algorithm are constructed based on L2 norm model, this single model is not suitable for different regions of the image and it cannot meet the requirement of super resolution reconstruction in the smooth and edge regions. The edge of the reconstructed range image may be over smooth, while the L1 norm model is favorable to reconstruct the sharp edges. Therefore, L_α(α=1 or α=2) norm model based on local content perception in distance fidelity and regularization terms is constructed to obtain rich texture details and sharp edges. It can be expressed as follows:

$$\begin{gathered} E_d(D) = \sum_{p \in M} |D(p) - G(p)|^\alpha \\ E_r(D) = \sum_{\mathrm{p}} \sum_{q \in N(p)} \frac{w_{pq}}{W_p} \left|D(p) - D(q)\right|^\alpha \\ \alpha = \left\{\begin{matrix} 2 & s(p) = s(q), \forall q \in N(p) \\ 1 & s(p) \neq s(q), \exists q \in N(p) \end{matrix}\right\} \end{gathered} \tag{9}$$

Firstly, SLIC is used to segment the super-pixel of high-resolution image *I*. At this time, each pixel in the image has different marks. Based on this, the division rules are as follows: suppose that each pixel in the neighborhood $N(p)$ of p has the same mark, and considers that point p is in the smooth region, then constructs the distance fidelity term and regularization term of L2 norm; when each pixel in the neighborhood $N(p)$ of point p is located have different labels, the distance fidelity term and regularization term of L1 norm are constructed.

4) High resolution range guided image based on partition interpolation

The distance similarity guide term and region similarity guide term of region similarity guidance algorithm are calculated by D_g. when the upper sampling multiple of bicubic interpolation method is too large, the edge of reconstructed range image is easy to blur by using the image to guide reconstruction, while the edge of the nearest interpolation image is sharper than that of bicubic interpolation image. Therefore, this paper proposes a method to obtain high-resolution guide image through the partition interpolation to improve the edge sharpness of the reconstructed image. The basic idea is to obtain high-resolution range profile by bicubic interpolation and nearest neighbor interpolation in smooth region and edge region respectively, it can be expressed as follows:

$$D_g(p,q) = \left\{\begin{matrix} D_s(p,q) & s(p) = s(q), \forall q \in N(p) \\ D_z(p,q) & s(p) \neq s(q), \exists q \in N(p) \end{matrix}\right\} \tag{10}$$

Where, D_s is achieved by bicubic interpolation, D_z is achieved by nearest neighbor interpolation.

5) Adaptive standard deviation of Gaussian kernel function

The standard deviation of Gaussian kernel function in the regularization term of regional similarity guidance algorithm cannot be adaptive, and the standard deviation of global simplification cannot adapt to the distance and gray level changes of different image neighborhood systems. Therefore, according to the adaptive idea proposed by Gangtao Hao and others, the standard deviation of adaptive Gaussian kernel function is introduced into the regularization term through certain improvement.

The standard deviation of adaptive Gaussian kernel function is based on local content perception. The standard deviation of adaptive Gaussian kernel function in color similarity guide term w_c, distance similarity guide term w_g and regional similarity guide term w_n is constructed as follows:

$$\sigma_c = l_c\left(1 - \frac{Sc - \min(Sc)}{\max(Sc) - \min(Sc)}\right)$$
$$S_c = \frac{1}{n_p - 1}\sum_{q \in N(p)} \left|\mu_c(p) - I(q)\right|^2 \tag{11}$$
$$\mu_c(p) = \frac{1}{n_p}\sum_{q \in N(p)} I(q)$$

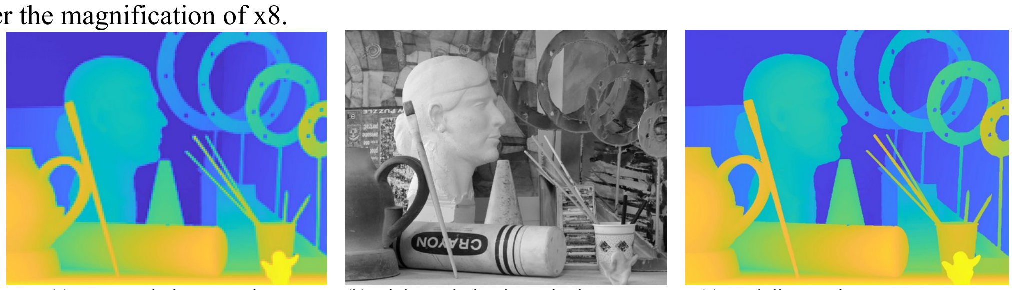
$$\sigma_g = l_g\left(1 - \frac{Sg - \min(Sg)}{\max(Sg) - \min(Sg)}\right)$$
$$S_g = \frac{1}{n_p - 1}\sum_{q \in N(p)} \left|\mu_g(p) - D_g(q)\right|^2 \tag{12}$$
$$\mu_g(p) = \frac{1}{n_p}\sum_{q \in N(p)} D_g(q)$$

$$\sigma_n = l_n\left(1 - \frac{Sn - \min(Sn)}{\max(Sn) - \min(Sn)}\right)$$
$$S_n = \frac{1}{n_p - 1}\sum_{q \in N(p)} \left|\mu_g(p) - \sum_{m \in \Omega(q)} h(m) D_g(q+m)\right|^2 \tag{13}$$
$$\mu_n(p) = \frac{1}{n_p}\sum_{q \in N(p)}\sum_{m \in \Omega(q)} h(m) D_g(q+m)$$

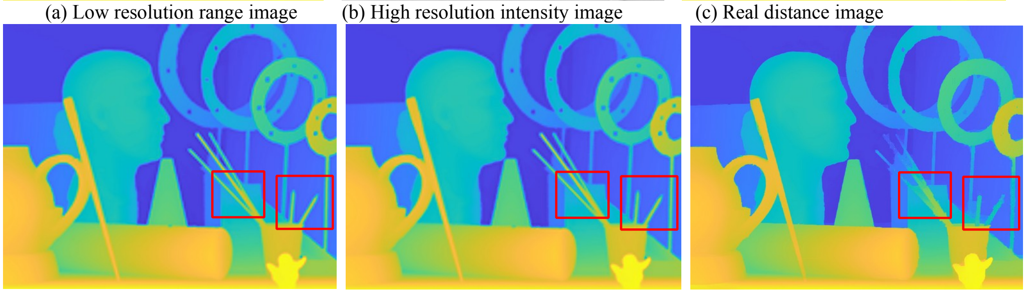
Where, n_p is total number of pixels in the neighborhood, $u_c(p)$, $u_g(p)$ and $u_n(p)$ are the average intensity value, the average distance value and the average regional similarity value of the neighborhood where the point p is located, S_c, S_g and S_n are the standard deviation of intensity value, distance value and regional similarity in the neighborhood of p, l_c, l_g and l_n control the sensitivity of w_c, w_g, w_n respectively.

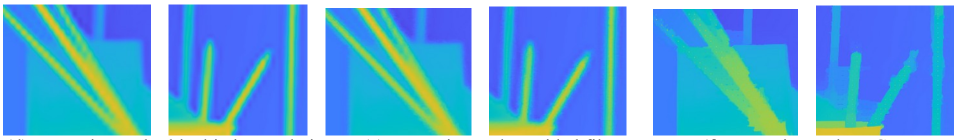
2 Verification of Middleburg dataset

The Middleburg dataset is used to evaluate the algorithm quantitatively. In order to verify the effect of super-resolution reconstruction, different factors (x2, x4, x8, x16) are used to down sample the range image to simulate the low-resolution range image. The algorithm in this paper is compared with bicubic interpolation, guided filtering, TGV, standard image guided algorithm and region similarity guided algorithm. Figure 2 shows the visual effect under the magnification of x8.



(a) Low resolution range image (b) High resolution intensity image (c) Real distance image





(d) Range image by bicubic interpolation (e) Range image by guided filter (f) Range image by TGV

Figure 2 Middleburg dataset processing results

Root mean square error (RMSE) and structure similarity (SSIM) are used to objectively evaluate the reconstruction results of different methods. The evaluation results are shown in Table 1.

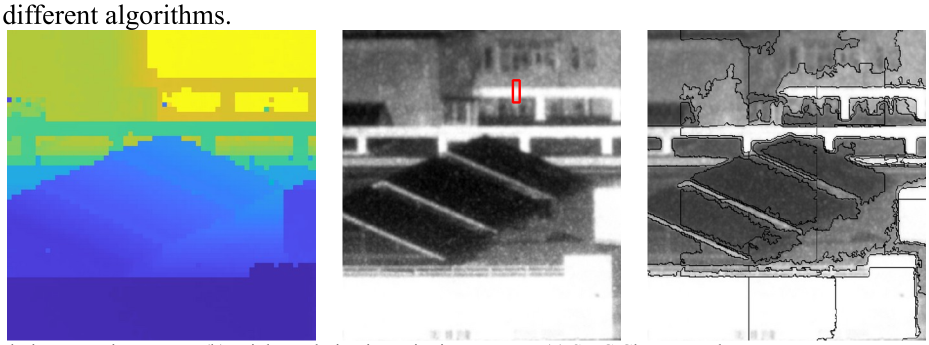
Tab 1 Comparison of reference image quality evaluation indexes of different methods

	X2	X4	X8	X16
	RMSE|SSIM	RMSE|SSIM	RMSE|SSIM	RMSE|SSIM
Bicubic interpolation	2.6|0.9996	3.85|0.9959	5.52|0.9741	8.36|0.902
Guided filter	3.0|0.9986	3.69|0.9957	5.22|0.9771	8.20|0.906
TGV	3.1|0.9974	3.83|0.9940	7.03|0.963	12.85|0.879
Guided by standard image	4.7|0.9798	5.16|0.9763	5.83|0.9682	7.69|0.936
Guided by regional similarity	2.5|0.9960	3.65|0.9947	5.18|0.9807	7.73|0.932
Our method	3.1|0.9941	3.83|0.9931	5.06|0.9813	7.45|0.939

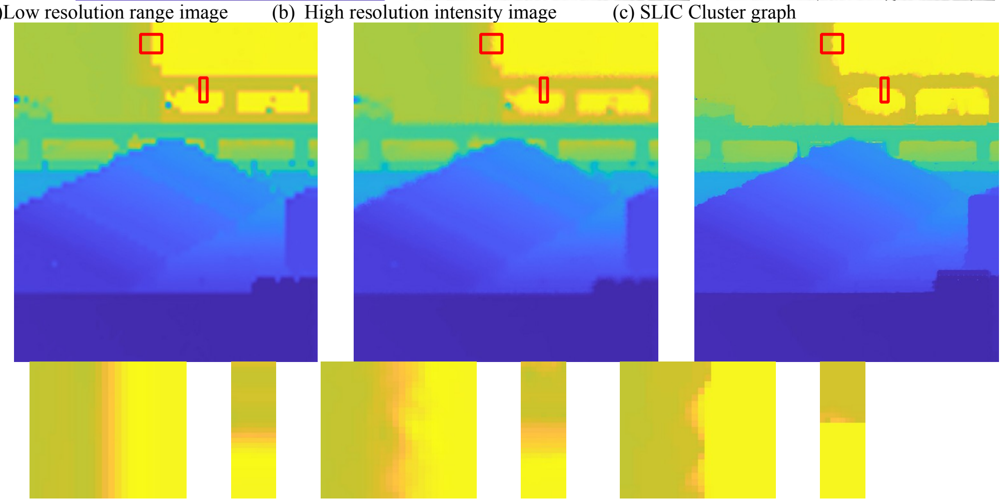
As can be seen from Figure 2, the reconstructed image of the algorithm in this paper has higher definition, richer detail information and sharper edge than other algorithms, and has less texture duplication than TGV and standard image guided algorithm. It can be seen from Table 1 that when the magnification is high, the lack of information such as edge contours at low resolution distance is more serious, the algorithm in this paper obtains the optimal index. When the magnification is low, the performance of the algorithm in this paper is poor. Compared with other algorithms, the RMSE and SSIM are improved by 72% and 7% respectively.

3 Verification of real experimental data

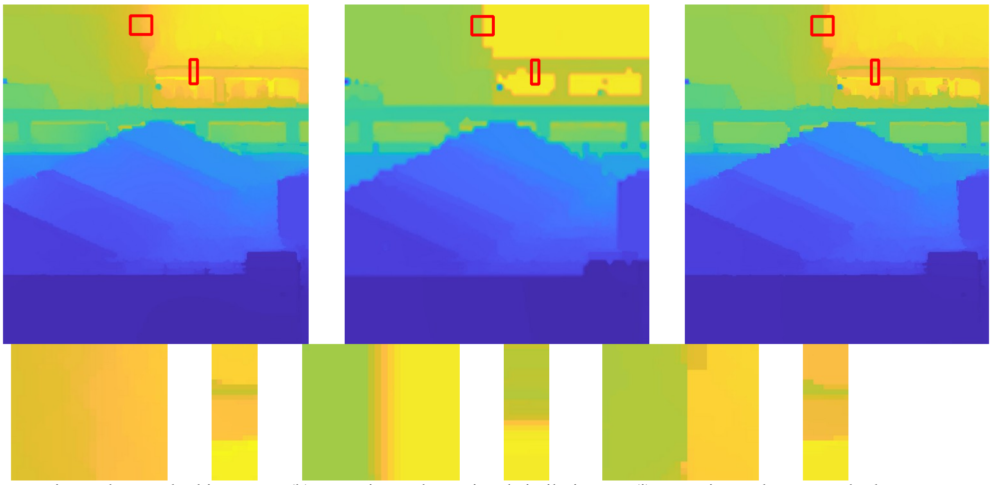
The real data collected by Gm-APD lidar and ICCD lidar are tested by super-resolution. The resolution of range profile acquired by GM APD lidar is 64 × 64, and that of intensity image acquired by ICCD lidar is 480 × 640. Due to different field of view, the resolution of range profile is 328 × 366 after registration. Figure 3 shows the visual effects of different algorithms.



(a)Low resolution range image (b) High resolution intensity image (c) SLIC Cluster graph



(d)Range image by bicubic interpolation (e)Range image by guided filter (f)Range image by TGV



(g) Range image by standard image (h)Range image by regional similarity (i)Range image by our method

Fig 3 Range image processing results of lidar

Three non-reference image quality evaluation indexes are used to objectively evaluate the reconstruction results of different methods. The evaluation results are shown in Table 2.

Tab 2 Comparison of non-reference image quality evaluation indexes of different methods

	Brenner gradient	Energy gradient	Laplacian gradient
Bicubic interpolation	276	105	2350
Guided filter	202	75	2347
TGV	459	295	2990
Guided by standard image	340	177	2570
Guided by regional similarity	292	123	2426
Our method	508	343	3081

It can be seen from Figure 3 that only the standard image guided algorithm and the algorithm in this paper can recover the actual thickness shape of the distant railing, and the reconstructed image edge of the algorithm in this paper is sharper. As can be seen from Table 2, the algorithm in this paper obtains the optimal index. Compared with other algorithms, Brenner gradient can be increased by 151%, energy gradient by 357%, Laplacian gradient by 31%.

The experimental results of simulation data and real data show that the performance of this algorithm is better than bicubic interpolation, guided filtering, TGV, standard image guidance algorithm and regional similarity guidance algorithm. For the low-resolution GM APD lidar 3D range profile, due to the lack of information such as edge contour, the low resolution range profile is more complete than the edge contour The results show that the algorithm has better performance in reconstructing image edge sharpness and recovering edge contour of low resolution range image.

4 Conclusion

In this paper, an improved image guidance algorithm for super-resolution reconstruction of 3D range profile is proposed by combining the 3D range profile of low-resolution GM APD lidar and the intensity image of high-resolution ICCD lidar. The experimental results of simulation data and real data show that the proposed method has higher accuracy of reconstruction data and higher edge sharpness of reconstructed image. In this paper, the algorithm needs to set multiple parameters, the selection of parameters has a great impact on the reconstruction results, so automatic parameter setting will be the next research direction.

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