Real-time Volume Estimation of Mass in Excavator Bucket with LiDAR Data

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Abstract -

In the autonomous excavation task, the real-time estimation of the bucket filling rate and the volume of the excavated mass are essential feedbacks to measure the excavation quality. In this work, facilitated by the LiDAR and inclination sensors mounted on an autonomous excavator, we introduce an online method to calculate the volume of the mass in the excavator bucket during digging process. The LiDAR is mainly used for acquiring the 3D point clouds of the excavated mass and bucket, and the inclination sensors are utilized for localization acquisition of the bucket. In specific, a pre-process is first used to obtain the empty bucket model by scanning it with LiDAR. Then, to reduce the influence of the noises of the inclination sensors in the digging process, a registration algorithm is employed to transform the real-time captured point clouds of the bucket and excavated mass to the empty bucket model (obtained in the pre-process). Finally, based on the height map construction and point clouds interpolation, volume estimation algorithm is utilized to obtain the final results. Note that our method is validated in real-world scenarios, and the experiment results demonstrate the accuracy and reliability of our volume estimation scheme.

Keywords -

Autonomous excavation; Volume estimation; Height map

1 Introduction

Recently, research and developments of autonomous excavation have seen increased popularity as it promises more efficient, more sustainable, and safer excavation operations (Zhang et al. [1], Jud et al. [2]). In the excavation process, important metrics to evaluate the excavate quality are whether the bucket is filled with excavated mass and how much it has been filled after each excavation. Previous methods, such as payload estimation [3], mainly utilize the measurement of hydraulic cylinder pressures and dynamic modeling for volume estimation by estimating the payload carried in a hydraulic excavator. However, these approaches usually require additional hardware sensors as well as sensor calibration, which limits the applications.

In this study, to relief the problem, we utilize visual strategies to directly measure the excavation quality considering current autonomous excavators are commonly equipped with cabin-mounted LiDAR and inclination sensors, while LiDAR sensors are mainly used for point clouds acquisition of surrounding environments, and inclination sensor for measuring the bucket pose. In this work, we address this problem by estimating the volume of the excavated mass in the bucket using LiDAR data on an autonomous excavator (Figure 1). Note that the data is acquired from LiDAR (e.g. Livox Mid100), which has an uneven distribution, and the volume estimation is especially challenging. Specifically, to estimate the in-bucket mass volume, firstly, the dense bucket point cloud is dynamically obtained by fusing multiple frames of bucket point clouds, and the bucket pose is acquired by the inclination sensors mounted on the excavator, simultaneously. We then align the real-time obtained bucket points with an initialized empty bucket model, and the height maps are generated and interpolated both on the real-time obtained bucket points and the empty bucket model. Finally, the mass volume is calculated based on the height maps.

In summary, this paper presents the following contributions:

- A dynamic bucket point cloud fusion method that allows obtaining the dense bucket point cloud while the bucket is moving, which is a base of real-time volume estimation.
- A height map interpolation method that makes it possible to estimate the volume from the height map on the uneven LiDAR data.

To the best of our knowledge, this is the first demonstration of the real-time in-bucket mass volume estimation on the uneven LiDAR data.

2 Related Work

A direct way to measure the excavation quality in real-time is to weigh the mass in the bucket. The method of payload estimation [3], which is based on cylinder pressures measurement and dynamic modeling, can estimate the payload carried by a hydraulic excavator. As we are in an autonomous excavator that can provide point cloud by the cabin-mounted LiDAR sensors and bucket pose by the

Figure 1. The autonomous walking excavator which is equipped with a cabin-mounted LiDAR(Livox Mid100) and a HIK web camera.

inclination sensor, it is possible to measure the excavation quality by visual methods.

Wulfsohn et al. [4] presented an estimator of the volume of axially convex objects from total vertical projections with the known position of the vertical axis. However, this approach needs to rotate the object around the known vertical axis and re-scanning it, which is not feasible in our task. Mayamanikandan et al. [5] presented a tree volume estimation method using terrestrial LiDAR data, based on the extraction of the tree diameter at breast height(DBH) using Random Sample Consensus(RANSAC) based circle fitting and the estimation of tree height. However, RANSAC based method is not suitable for the mass which has an irregular shape in the bucket. Be Wley et al. [6] presented a model and reconstruction based volume estimation method to measure the in-bucket payload volume on a dragline excavator. However, their approach focuses on bucket classification and reconstruction from the 2D scanlines, which is very different from LiDAR data.

3 Volume Estimation Pipeline

As the goal here is to dynamically calculate the volume of the mass in a moving excavator bucket, we are looking to get a dense and up-to-date bucket point cloud as well as the latest bucket pose in the LiDAR coordinate system. This section presents a dynamic bucket obtaining pipeline that uses the excavator's onboard LiDAR sensors and the joint states to fuse multiple frames of bucket point clouds incrementally. We first scan and initialize the empty bucket model, which is used to align with the real-time obtained bucket points and as a base of volume estimation. A height map and interpolation based volume estimation module is then presented. An overview of the different modules constituting the volume estimation pipeline is depicted in Figure 2.

3.1 Dynamic Bucket Obtaining

With the aim of providing a bucket point cloud as complete as possible, we intend to fuse multiple frames of bucket points to get a dense bucket point cloud. To this end, we initially acquire the bucket pose from ROS transformation tree(TF) corresponding with the current frame point cloud. We then segment the point cloud by the radius search to extract the bucket point cloud. After about 10 frames of the bucket point cloud are obtained, we fuse them by transforming them through the original pose. Thus, the dynamically dense bucket can be expressed as:

$$B = \{T_i^{-1} B_i | i = 1, 2, ..., N\} \tag{1}$$

Where B is the dense bucket point set, N is the number of the frames, T_i is the current bucket pose, B_i is the segmented bucket point set in frame i.

3.2 Pose Initialization

It is easy to recover the bucket to the original pose by transforming it with the latest transformation matrix. Furthermore, it is necessary to initialize the empty bucket model to parallel to the axis for the convenience of bucket part removing and height map generation. We initialize the model with principal component analysis(PCA) results and fine-tune it by hand. The initialized empty bucket model is shown in Figure 3:(b) where the plotted grid represents the XOY plane. Thus, we got the transformation from the original pose to initialized pose T_p, and the initial transformation from scene to model can be expressed as:

$$T_{init} = T_p T_l^{-1} \tag{2}$$

Where T_{init} is the initial transformation, T_l is the latest bucket pose obtained from TF.

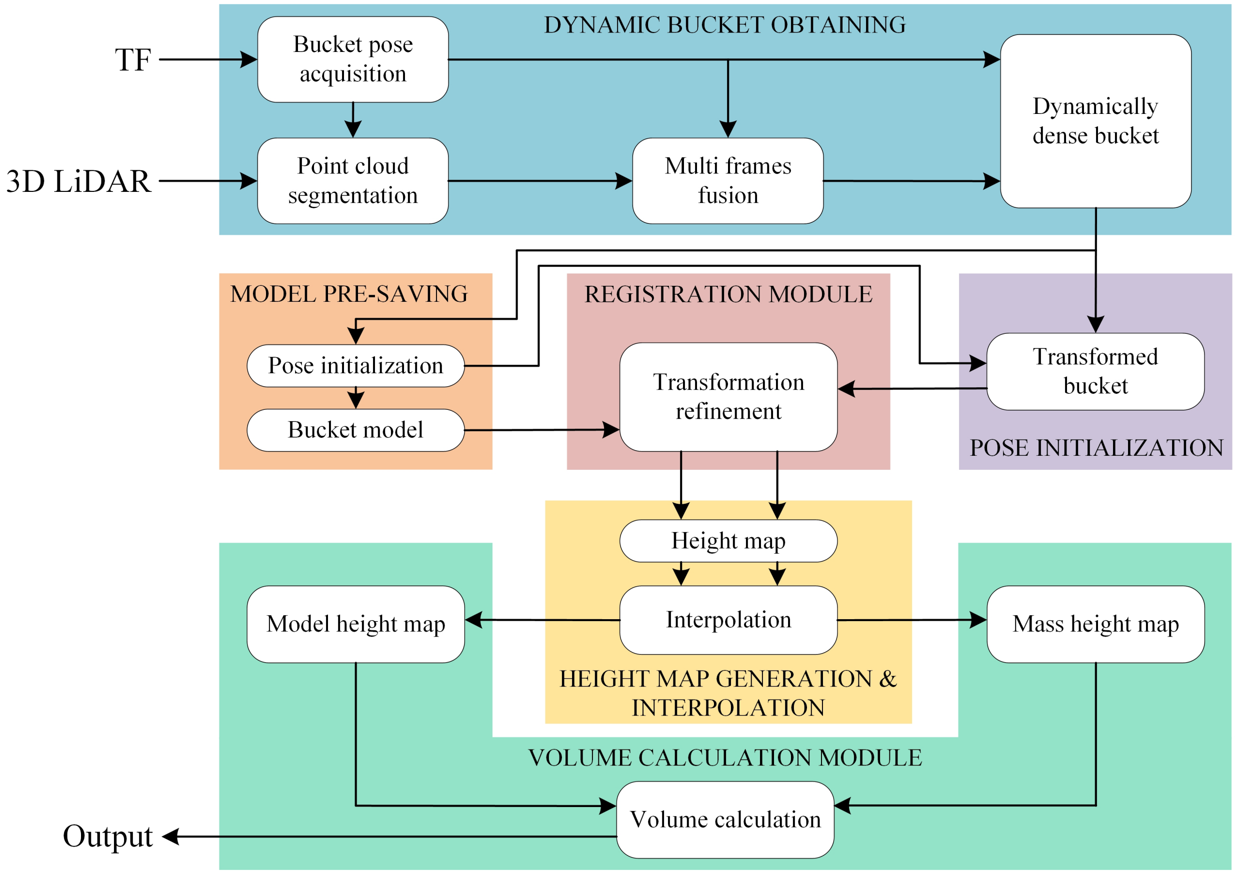

Figure 2. Overview of the volume estimation pipeline developed for the volume estimation of the mass in an excavator bucket.

3.3 Transformation Refinement

The registration module gives the volume estimation system the ability to align the real-time obtained bucket points with the model, which can improve the accuracy of volume estimation.

Our registration approach aims to find the transformation that minimizes the distance between the empty bucket model and the real-time obtained bucket points with an initialized pose provided by the inclination sensors. Considering this case, the iterative closest point(ICP) is suitable for the transformation refinement. As there is lots of noise produced by the moving bucket in the real-time obtained bucket points, the bucket point cloud is firstly filtered using a uniform down-sample, and then filtered by a statistical outliers removal. We retain the original bucket point cloud for the next height map generation step. Then, an ICP step is employed to refine the alignment of the empty bucket model and real-time obtained bucket points, yielding an improved transformation T_{icp}. The final transformation between the empty bucket model and real-time obtained bucket points is then computed as follows:

$$T_{final} = T_{icp} T_{init} \tag{3}$$

3.4 Height Map Generation and Interpolation

In our implementation, we generate the height map using the height of points on the z-axis directly, facilitated by the pose initialization step, and those values are stored in a plotted grids based on the minimum and maximum points on the x-axis and y-axis.

Before we generate the height map from the real-time obtained points, we first removed the most bucket part of the real-time obtained bucket points using a passthrough filter. The point cloud of mass in the bucket is then used for height map generation. We use the full point cloud to generate the height map on the empty bucket model(Figure 3:(b)), which is shown in Figure 3:(c).

As shown in Figure 3:(c), there are lots of holes in the generated height map produced by the distribution of LiDAR points. Those holes must be filled by the interpolation method, while each hole means an invalid value in

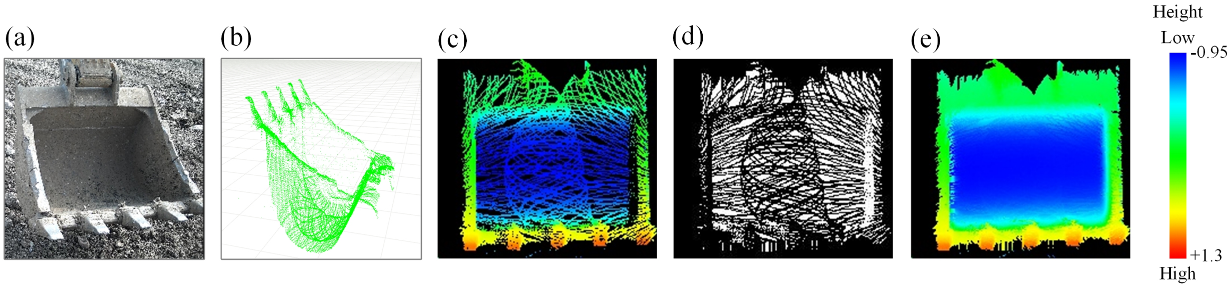

Figure 3. The height map generation and interpolation process: (a) the empty bucket image, (b) the initialized empty bucket point cloud, (c) the generated height map, (d) the interpolation area(white), (e) the interpolated height map.

the volume estimation module. The proposed approach of interpolation consists of the following steps:

1) Interpolation area selection: To interpolate correctly, the first step is to know which pixel needs to be interpolated, which is very important for volume estimation because false interpolation means reducing the accuracy. We firstly check the bordering points on every row and every column, which are shown in Figure 4, marked as red points. Then, the interpolating points are determined by judge whether it is within the bordering points and whether there are points in its adjacent region. We change the size of the adjacent region to fit the density variation. The interpolation points are marked as blue points in Figure 4. The selected interpolation area of the model height map is shown in Figure 3:(d).

2) Interpolation: As the interpolation area is selected, we compute the mean height of the valid points in the adjacent region of every interpolating points, and set the value of the interpolating point as h_{mean}, which can be expressed as:

$$h_{mean} = \frac{1}{N}\sum_{i=1}^{N} h_i \tag{4}$$

Where N is the number of the valid points, h_i is the height of i_{th} valid point in the adjacent region. The interpolated model height map is shown in Figure 3:(e).

3.5 Volume Estimation

The volume estimation module is based on the interpolated height map both on the empty bucket model and the real-time obtained bucket points(Figure 6:(e)). We compute the difference between the height maps of the empty bucket model and the real-time obtained bucket points on every pixel, where the values are valid on them at the same time, which can be expressed as:

$$d = h_s - h_m \tag{5}$$

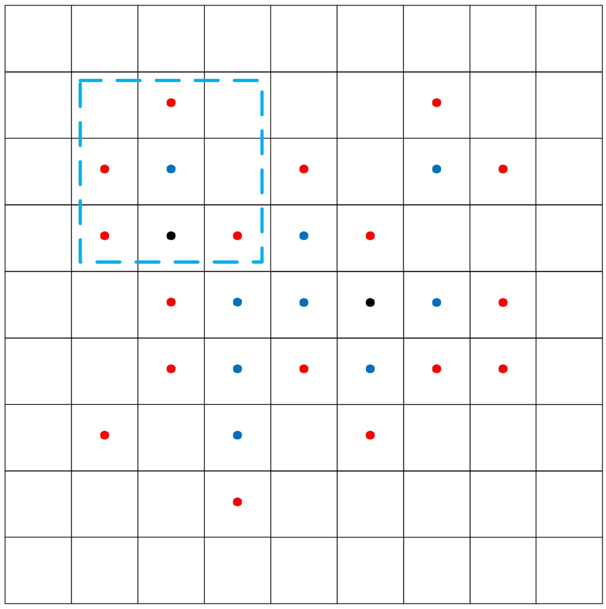

Figure 4. The interpolation area selection, red: the edge points, black: the inside points, blue: the interpolation points.

d is the difference between the height h_m and the height h_s on the height maps of the empty bucket model and the real-time obtained bucket points on every pixel. The diagram of the difference is shown in Figure 5, which is a side-section of the empty bucket model and the mass.

Considering the size of the plotted grids, we compute the volume of the mass in the bucket as follows:

$$V = \sum_{d \in P_{valid}} (l_{grid}^2 \times d) \tag{6}$$

Where V is the calculated volume, P_{valid} is the valid pixels, l_{grid} is the length of the grid, d is the difference of the valid pixels.

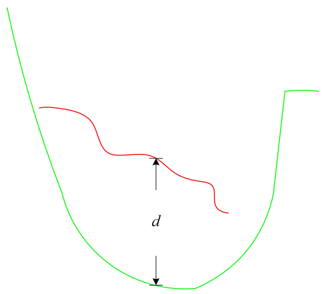

Figure 5. The difference calculation in the side-section, red: the mass, green: the empty bucket model.

4 Experiments

To show the applicability and repeatability of the presented system, we implemented the different modules using the robotic operating system [7] and integrated them on the autonomous excavation system to perform the volume estimation of the mass in the excavator bucket, which is tested randomly in the field.

4.1 Bucket Obtaining and Pose Initialization

Figure 7 illustrates the process of multiple frames fusion of dynamic bucket point clouds and the initialized pose, which have been discussed in Section 3.1 and Section 3.2 respectively.

4.2 Transformation Refinement

With the bucket pose acquired by TF and a fixed transformation from the original pose to the initialized pose, we aligned the real-time obtained bucket points and the model with an error which is caused by the low accuracy of the sensors. After the down-sample and the outliers removal processes, an ICP step is then employed to refine the alignment. In our experiments, a large nearest point search radius leads to a false registration result while the mass entirely shades the bucket. Considering the maximum distance error is about 3 cm, we set the maximum correspondence distance to 3 cm to avoid false registration.

4.3 Height Map Generation and Interpolation

As 10 frames of bucket point cloud have been fused dynamically and the fused bucket point cloud has been aligned with the model successfully, we generate the height maps and interpolate them with the method discussed in Section 3.4 both on the real-time obtained bucket points and the empty bucket model. As it has been shown in Figure 6:(e), there are some not interpolated points which are resulted from the open form distribution of the points on the height map. The most relevant parameters of the experiment are summarized in Table 1.

Table 1. Main parameters of the volume estimation pipeline

Bucket segmentation	
Search radius	1.5m
Down sample	
Voxel size	0.01×0.01×0.01(m)
Outliers removal	
Number of nearest points	100
Multiplier of the std. dev.	0.8
ICP	
Normal estimation radius	0.025m
Max. correspondence dist.	0.03m
RMSE threshold	0.01m
Height map generation	
Grid size	0.01×0.01(m)
Interpolation area selection	
Adjacent region size	8×8(pixels)
Height map interpolation	
Adjacent region size	5×5(pixels)

Abbreviations: ICP, iterative closest point; RMSE, root mean square error;

4.4 Volume Estimation

As the height map generated and interpolated, we calculate the volume of the mass in the bucket using the method discussed in Section 3.5.

Table 2. Mean computation times and standard deviations (in ms) of each step involved in the volume estimation pipeline, as computed on an Intel Core(TM) i7-10875H CPU

Submodule	Time
Bucket segmentation and fusion	46±11
Down sample	3±1
Outliers removal	286±7
ICP	
Normal estimation	20±6
Alignment	83±15
Height map generation	<1
Interpolation area selection	2±1
Height map interpolation	5±1
Volume estimation	<1
Total	539

For the sake of completeness, in Table 2 we report the computational times of the individual steps in the volume estimation pipeline, when executed in a single thread on a Core(TM) i7-10875H CPU. As it can be observed, the complete volume estimation routine is executed in approximately 0.5s in our experiments, which makes our approach suitable for online operation.

As there is not a convenient way to get the ground truth, we firstly generated a height map of the full bucket, which is shown in Figure 8, and calculate the full bucket volume

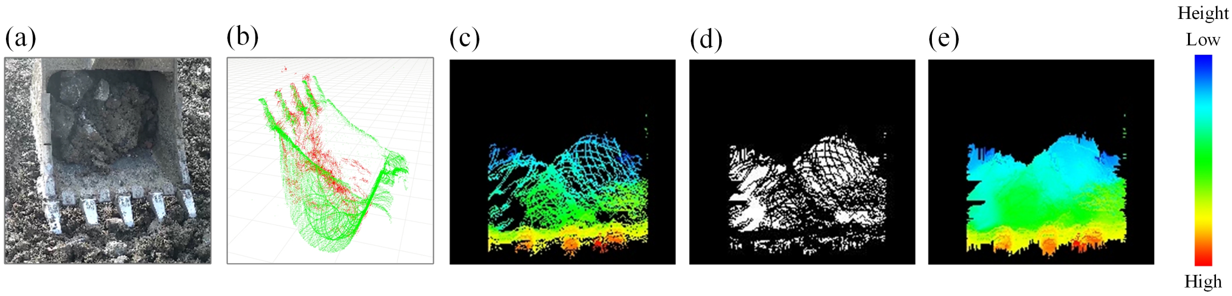

Figure 6. The height map generation and interpolation on the real-time obtained bucket points: (a) the bucket with mass image, (b) the mass point cloud (red) and the empty bucket point cloud(green), (c) the generated height map of the mass, (d) the interpolation area(white), (e) the interpolated height map.

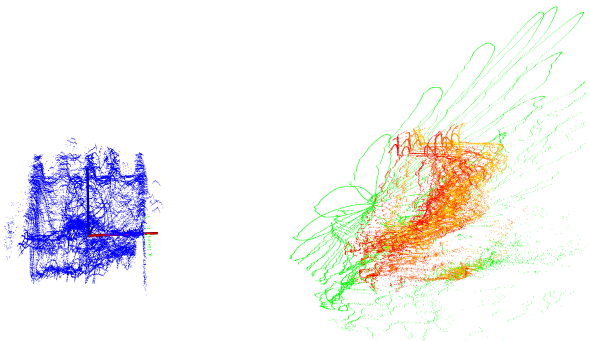

Figure 7. Multiple frames of bucket obtaining, green: single frame of the background point cloud, red: the segmented bucket point clouds of 10 frames while the bucket is moving, blue: fused and initialized bucket point cloud of multiple frames.

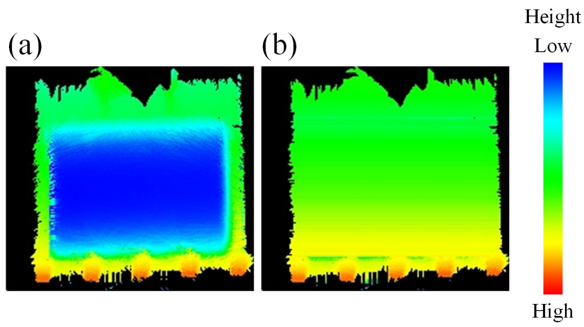

Figure 8. Full bucket volume estimation, (a) the empty bucket height map, (b) the generated full bucket height map.

as V_{full}. In our experiment, $V_{full} = 1.71m^3$. Then, we compute the filling rate of the bucket comparing with the directly observed filling rate to measure the accuracy of our approach. The filling rate is computed as $R = \frac{V_{est}}{V_{full}} \times 100\%$, where V_{est} is the estimated volume of the mass in the bucket in Equation 6.

Figure 9 illustrates five times volume estimation processes, we compare the volume estimation results(in filling rate) with the directly observed filling rate, which is shown in Table 3.

Table 3. Volume estimation results comparation in filling rate

Experiments	Observed	Estimated
1	0%	0.93%
2	50%	47.51%
3	70%	72.16%
4	105%	107.35%
5	115%	110.86%

As it can be observed, our approach gets the expected results on volume estimation. In Experiment 1, the estimated filling rate of the empty bucket is 0.93%, caused by the alignment error and the noises. In Experiment 5(e), there is a not scanned area resulting a lower volume estimation result.

5 Conclusion

This article introduces an integrated in-bucket mass volume estimation system for the autonomous excavation quality measurement with a robotic excavator. The core of the volume estimation pipeline constitutes of a height map generation and interpolation module which is based on the dynamic bucket points obtaining and transformation refinement. And the experiment result shows the applicability and reliability of the presented system.

A limitation of the current system is that the model based volume estimation process always ignores the points outside the model on the height map. It means that the volume will not be calculated when objects are extended out the bucket side, such as the stones. As LiDAR collects the

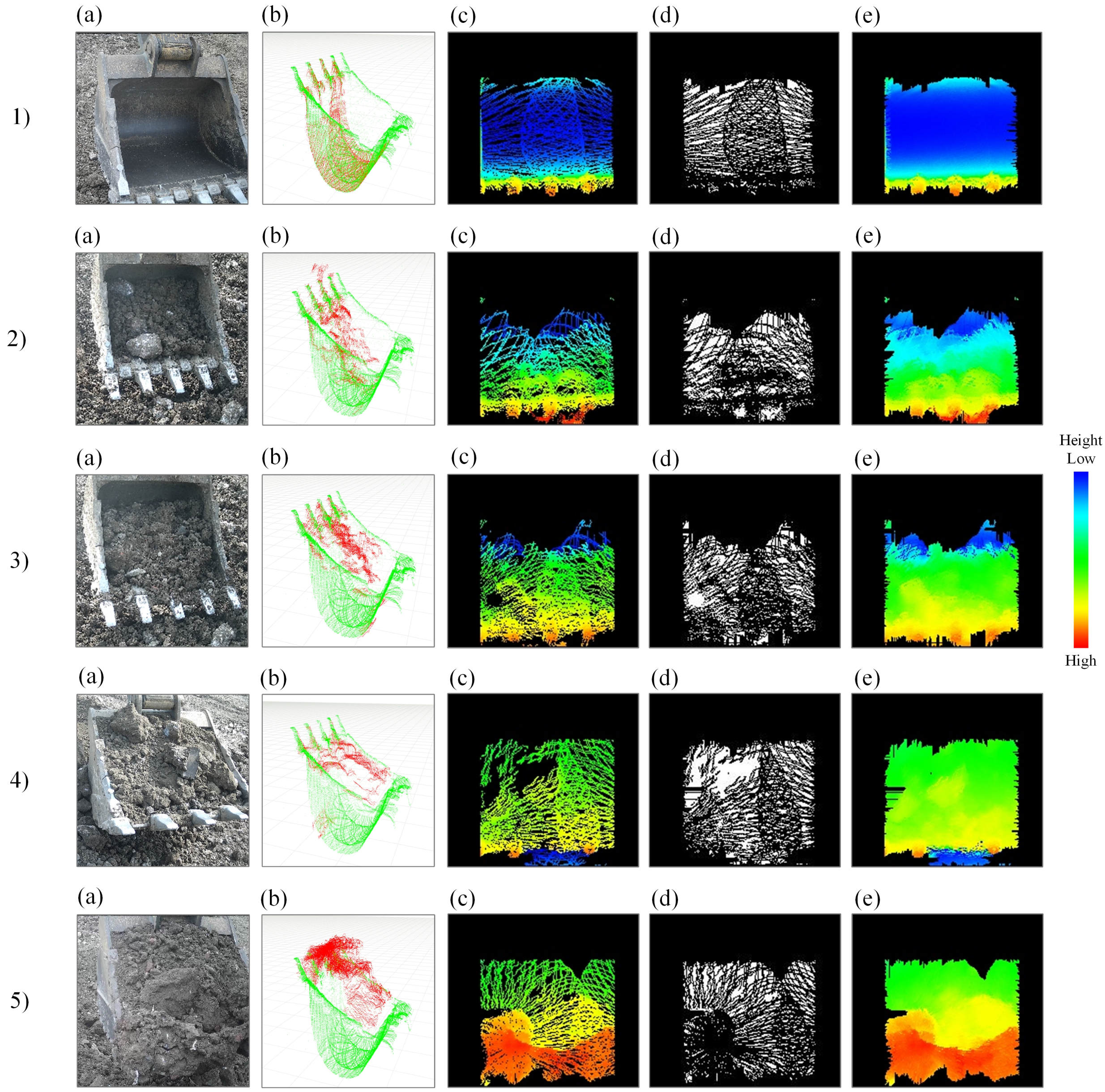

Figure 9. The generated and interpolated height maps on real-time obtained bucket points, (a) the bucket with mass image, (b) the mass point cloud (red) and the empty bucket point cloud(green), (c) the generated height map of the mass, (d) the interpolation area(white), (e) the interpolated height map.

data, another limitation is that the dynamically obtained bucket point cloud will be full of noises which are the flied-out points when the bucket is moving fast, especially when moving away from the LiDAR. As it can be observed in our experiments, the existence of noise leads to the reduction of accuracy, especially when ICP is employed. Thus, a future research direction of our approach is the noise suppression.

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