Self-Position Estimation for Virtual 3D City Model Construction with the Use of Horizontal Line Laser Scanning

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This paper proposes a novel notion of spatio-temporal range image and an efficient way to construct 3D geometric model of urban scene with the use of this range image. We mount vertical and horizontal line-scanning laser range finders on our vehicle. The vertical one is for acquiring the scene geometry itself, and the horizontal one is for self-positioning of the vehicle. Laminating horizontal-scanning data along time axis, we can get a spstio-temporal range image which simulatneously represents spatial feature and temporal continuity of the scene geometry. Analyzing this range image, we can estimate the velocity or the self-position of our vehicle without using any external devices as GPS or INS. With this information, we can align the position of the vertical scanning lines and construct a proper 3D model of urban scene.

Keywords: *City scanning, 3D geometry model, Range image, EPI, Self positioning, Alignment*

1. Introduction

Construction of a 3-D geometric city model in a virtual world has become a highly interesting research topic among many research fields such as computer vision/graphics, virtual/mixed reality, sensing, architectonics, etc. In particular, urban environment models are expected to be applied to various fields, including urban planning, disaster prevention, and intelligent transport systems.

However, the geometry or textures of extensive environments such as urban scenes cannot be scanned by a single sensing device at one time because of either occlusion or a resolution problem with current commercially available sensing devices. One general solution is to repeat "stop-and-go" as [3], that is, scan from one fixed point and move to another fixed point repeatedly, where the data is merged after whole scanning. Although this approach gives a relatively dense and accurate scanning result, it takes a long time to apply it to extensive environments like urban scenes.

A powerful way to solve the problems of this approach is to scan objects with a sensor that is mounted on some kind of movable body, e.g., a vehicle, a helicopter,or an airplane. This method is relatively efficient and suitable for scanning extensive areas; however, the ego-motion or the velocity of the scanner must be obtaind by some kind of technique.

The most popular solution for this problem is to mount other external devices such as global positioning system (GPS) or inertial navigation system (INS) on the scanning vehicle[4]. It is a very simple, convenient technique; however, the accuracy of the positioning result depends on the condition of the radio wave signnal, especially on the reception situation. The accuracy is not sufficient at the ground level of urban areas where there is occulusion by buildings or raised expressways.

Another approach has been proposed by C.Frueh et al.[5]. They mount a line-scanning laser range finder on the data acquisition vehicle, and let it sweep horizontal scanning lines. By matching each result of the scanning frame pairwise, the ego-motion of the data acquisition vehicle can be acquired. They constructed 3-D virtual textured model of an urban space by using this technique[6, 7].

Our strategy agrees with the attitude of this approach, that is, external devices such as GPS are suitable for acquiring the initial or macro position of the scanner. The detail or micro position is acquired by computational process of acquired geometric data from the viewpoint of computer vision. In concrete terms, the positional information is acquired by the horizontal-scanning laser range finder on our data acquisition vehicle in a similar way. However, in contrast to [5], one of the characteristic aspects of our approach is that our process allows for temporal continuity per scanning frame, not for pairwise matching.

Meanwhile, also in the field of mobile robotics this kind of problem has been studied for over 15 years as simultaneous localization and mapping (SLAM). The dominant approach to the SLAM problem was introduced in a seminal paper by Smith[8]. This paper proposed the use of the extended Kalman filter (EKF) for incrementally estimating the posterior distribution over robot pose along with the positions of the landmarks in outer environments. In the last decade, this approach has found widespread acceptance in the field of robotics, as tutorial paper documents[10]. Recent research has focused on extending this approach to larger environments with a speeding up algorithm[11, 12, 13].

These approaches are similar to the problem configuration in our approach; however, they are basically conformed on a sequential/incremental framewise process together with robot control signals as inputs. Moreover, in the case of mobile robots, there are no constraints on 2-D movements except obstacles and it is permissable to scan anew landmarks that were scanned in the past, where our method assumes a situation in which the scanning vehicle runs along a street, permitting movements due to an amount of lane-changing. Our method can reduce localizing errors in such situations.

We propose a novel notion of spatio-temporal range image from epipolar plane image(EPI), which is a classical analysis method of moving image. Spatio-temporal range image can simultaneously represent spatial features and temporal continuity. We estimate the self-position of our data aquisition vehicle by analyzing it.

2. Spatio-temporal range image

In this section, we introduce a novel notion of spatio-temporal range image . This is a range image which simultaneously represents both spatial features and temporal continuity. Its notion is derived from the EPI. Here we first explain the EPI analysis, and next explain the spatio-temporal range image .

2.1. Epipolar plane image

Epipolar plane image (EPI) analysis[1, 2] is one of the well-known methods for analyzing moving images, especially in the field of computer vision. EPIs can be created by moving a “line” camera (1 pixel height) horizontally and stacking each image frame vertically (or alternatively by the cross section of a stacked frame of an ordinary 2-D video image). As shown in Fig.1, when the camera moves

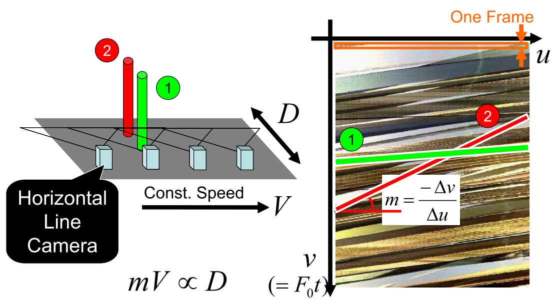


Figure 1: Epipolar plane image (EPI)

horizontally, pixels in each frame of the EPI which represent same point in real world compose a continuous edge. The edge image contains various amount of slope. These varieties of the slopes are derived by the parallax, which is the result of the difference of horizontal positions of the camera. Fig.2 represents the change of parallax when the camera moves from C_1 to C_2.

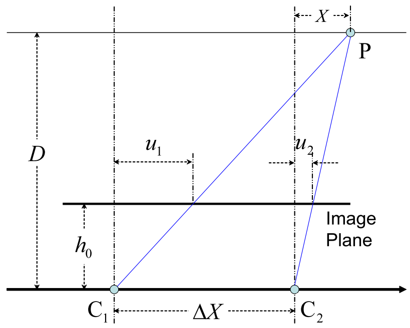


Figure 2: Relation between depth and parallax

From this figure, the depth D of Point P, a horizontal distance from the camera, and the parallax u are related with moving distance ΔX.

$$\Delta U = u_2 - u_1 = \frac{h_0 X}{D} - \frac{h_0(\Delta X + X)}{D} = -\frac{h_0}{D}\Delta X \tag{1}$$

And the slope of the edge m is related to the depth D of the point which composes the edge as follows:

$$m = \frac{-\Delta v}{\Delta u} = \frac{-F_0 \Delta t}{-\frac{h_0}{D}\Delta X} = -\frac{F_0}{h_0} \cdot \frac{D}{V} \tag{2}$$

where V, and F are the moving velocity and the frame rate of the camera, respectively.

By using this equation, D can be estimated from m and V, that is, the geometry of the object is reconstructed to some extent.

Edge detection is usually processed through image binarization and Hough transformation. Therefore, a camera is supposed to move at a constant speed in an EPI analysis.

2.2. Spatio-temporal range image

Here we propose the notion of spatio-temporal range image and describe its features, uses, and positioning among other existing techniques.

2.2.1. Definition and feature

Spatio-temporal range image is a range image which is created in a similar way as EPI, where the sensing device is not a line camera but rather, a line-scanning laser range sensor (Fig.3).

The feature is that stri simultaneously represents both the spatial characteristics of the object and the temporal continuity derived by scanning with continuous movement. In this range image, the slope of the edge directry

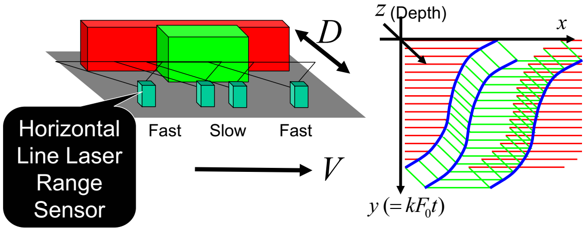


Figure 3: Spatio-temporal range image

represents the movement of the sensor as follows:

$$m = \frac{-\Delta y}{\Delta x} = \frac{-kF_0\Delta t}{-\Delta X} = \frac{kF_0}{V} \qquad (3)$$

where V, ΔX, F_0 are velocity, moving distance, scanning rate of the sensor, and k is an interval between each frame in stacking them along a temporal axis.

Table 1: EPI and spatio-temporal range image

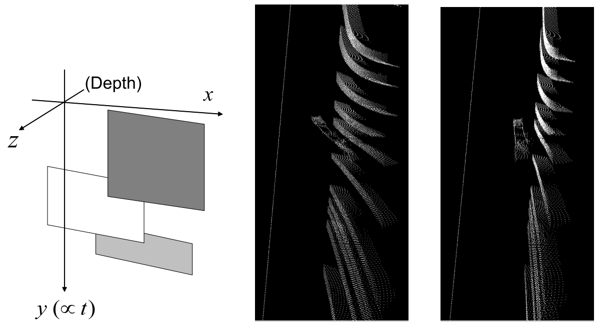
		EPI	Spatio-temporal range image
(a)	Scanning device	Camera	Range sensor
(b)	Depth information	Unknown	Known
(c)	Depth and slope of the edge	Dependent	Independent
(d)	Arrangement of pixel/point in the image	Even (Grid)	Uneven (Make clusters)

In addition, spatio-temporal range image has several features compared with EPI as Table 1 shows. (b) is due to the essential feature of the sensing device, range sensor, (c) is because a range sensor does not have a projection plane as a camera. (d) means that an EPI, a color/grayscale image, has a grid alignment of pixels while spatio-temporal range image does not have such an alignment. However, each point in spatio-temporal range image composes some cluster planes (Fig.4). This is because the objects are scanned with overwrap per each scan, in addition to (b).

2.2.2. Analysis and use

An unknown variable in EPI is the depth value of each pixel; it can be estimated by the slope of the edge in the EPI and the moving speed of the sensor as Equation 2 shows. Usually the camera is assumed to move in a uniform straight direction because of the difficulty of robust edge extraction in color/grayscale image with the exception of straight lines.

On the other hand, depth values of each point are known amounts in spatio-temporal range image . Though the slope of the edge in the range image has no relation with the depth value, the moving speed of the sensor V



(a) (b) (c)

Figure 4: Cluster planes composed of each range point in spatio-temporal range image . (b)(c) are side views of Fig. 7(a).

has a relation as described in Equation 3. Therefore, we can consider to estimate the moving speed of the sensor an unknown amount from the slope of the edge. Since each point in spatio-temporal range image composes cluster planes, these planes are not difficult to separate geometrically; hence its edge is relatively easy to extract even if not straight. This means that we can estimage time rate of change of the velocity, not a constant value. Besides, since the distance to the object is obtained from spatio-temporal range image , the moving path of the sensor can be estimated even if it is curved. As described, horizontal laser scanning can be used for ego-motion estimation through spatio-temporal range image analysis. The concrete process is described in the next section.

2.2.3. Positioning of spatio-temporal range image

Here, spatio-temporal range image as a vision technique is considered to be positioned as Table 5. Stereo matching is a technique to reconstruct 3-D geometry by detecting reference points from two color/grayscale images (area images). EPI is a notion that these two images become multiple line images with temporal continuity. Reference points are detected in a line detecting process, with the consideration of temporal cotinuity. On the other hand, alignment is a technique to obtain positional relation by detecting reference points from two range images (area images). Spatio-temporal range image is a notion when these two range images become to multiple line images with temporal cotinuity. Reference points are detected by an edge extracting process, with the consideration of temporal cotinuity.

3. Ego-motion estimation for urban space modeling

In the previous section, we introduced spatio-temporal range image and described how the motion of the sensor

Figure 5: Position of spatio-temporal range image

	Color/Grayscale Image	Range Image
Two area image, discrete	Stereo matching	Alignment
Multi line image, continuous	EPI	Spatio-temporal range image

can be estimated by analyzing it. In this section, a concrete technique for the estimation is described and our data acquisition system for 3-D geometry reconstruction is introduced.

3.1. Estimation algorithm

Here we explain the concrete algorithm for sensor motion estimation. This time, we assume that the sensor is mounted on a vehicle and moves at a variable speed but in a straight line. Fig.6 shows the process of estimatating sensor velocity and position. The details of the process are described in the following.

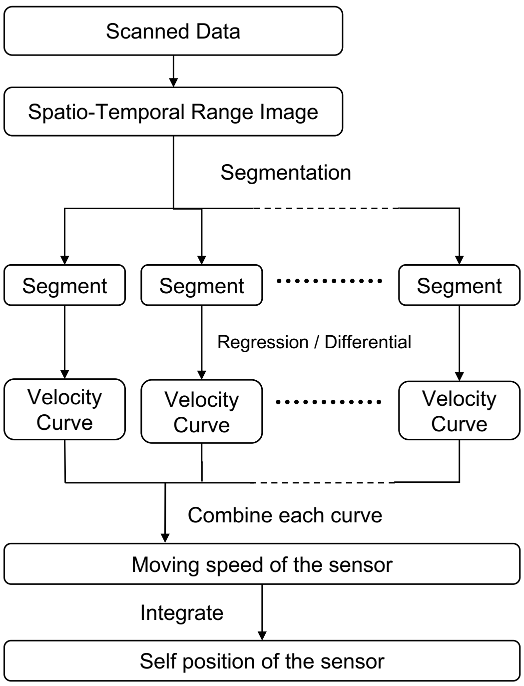


Figure 6: Flow of the estimation process of sensor velocity and position

Step 1.

Obtain spatio-temporal range image by vertically arranging horizontal scanning range data per each frame.

Step 2.

Segment each clusters in the spatio-temporal range image . As described in the previous section, each point in the range image actually makes a cluster as shown in Fig.4. Examples of segmentation results are shown in Fig.7. These images are front views of spatio-temporal range image , where x, y axes in Fig.3 correspond to horizontal, vertical axes in Fig.7 and z axis corresponds to grayscale value. Each segment represents transition of the sensor.

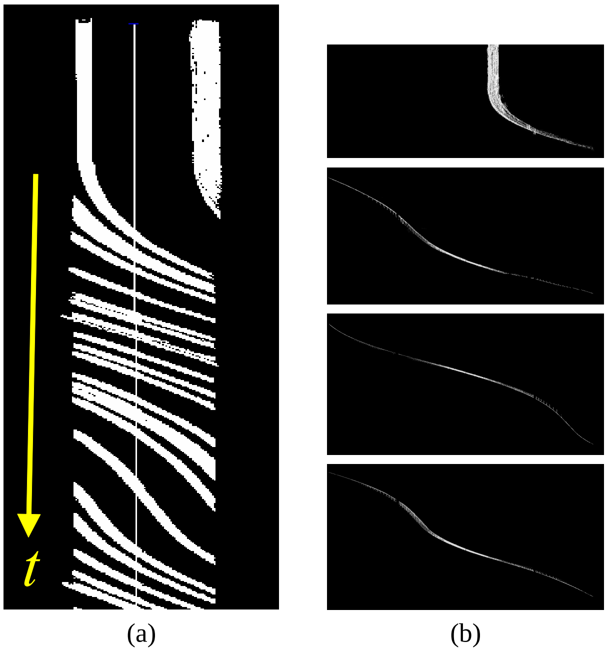


Figure 7: Segmentation of spatio-temporal range image . (a)Front view of original range image. (b) Segmented result.

Step 3.

Fit an analytical curve to each segment. In each segment, the scanned objects are represented as gradually moving, which is equivalent to the motion of the sensor itself. Actually, however, the segments are not composed of even planes because of scanning noise. Additionally, scanned range points are discretely distributed and the segment edges are not smooth since the resolution of scanning angle or scanning frequency is finite.

On the other hand, the range sensor is mounted on a vehicle in this research. Generally, the movemant change of a vehicle is considered to be smooth due to its mechanical acceleration principle as long as intentional sudden acceleration or stop is not carried out. To get the general tendency of transition, we propose to carry out the regression analysis and fit an analytical function to each segment, for vehicles can be assumed to make continuous and smooth movement in general.

Step 4

Though the regression curves describe the positional transition of the sensor, it is only in each segment that they remain valid. The segments are separated and therefore it is impossible to obtain the transition from start to end directly. Since each curve is expressed in analytical equation, we can estimate the moving velocity of the sensor per each segment by differentiating each curve. By smoothly connecting the differential of the curves, the time variation of the velocity from the start point to the end point is obtained. Finally, by integrating the time variation of the velocity, we obtain the transition history of the vehicle. Using the positioning information, we can align the vertical scanning line according to the correct position, even if the velocity varies.

3.2. System configuration and reconstructin of urban scene

Fig.8 shows our data acquisition vehicle. Four line-scanning laser range sensors are mounted on the vehicle. One is mounted in a direction that the sensor repeats sweeping horizontal scanning lines so that we can get spatio-temporal range image . The other three sensors are mounted in a direction so that the sensor repeats sweeping vertical scanning lines so that we can get actual geometry of buildings, etc., with each azimuth angle to reduce occlusions. Table 2 shows the specification of the laser range sensor. Laser class formulated by JIS is 1, which is eye-safe[15].

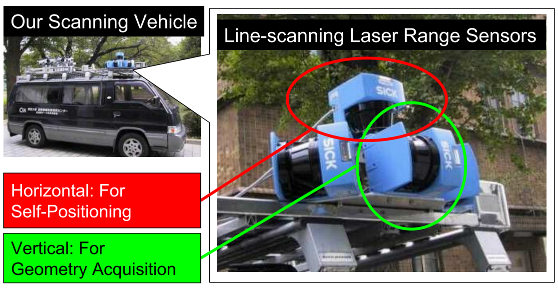


Figure 8: Our data acquisition vehicle

Table 2: Specification of the laser range sensor

Scanning principle	Time-of-flight
Scanning rage	37.5 Hz max
Scan angle	100°/ 180°
Scan angle resolution	0.25°/ 0.5°/ 1.0°
Measuring resolution	10mm
Measuring accuracy	± 35mm
Laser class	1
Manufacturer	Sick AG[16]

3-D model of objective scene can be reconstructed by arranging vertical-directional scanning lines to appropreate positions. When the vehicle travels at an arbitrary unknown speed, the result of the arrangement becomes expanded or shrunken before motion estimation,assuming that the vehicle had traveled in a constant speed. Through the motion estimation process proposed in the previous section, the arrangement result becomes appropriate.

4. Experiment and discussion

4.1. Outdoor experiment

We have made an outdoor experiment to confirm that our alogrithm works well. The experiment location was our campus, the Institute of Industrial Science, The Univ. of Tokyo (Fig.9). This time we assumed a linear motion to the vehicle, parallel to the wall of our building.

Figure 9: Test scene (photo of our campus building): vertical columns are actually arranged at every 6m.

Our data acquisition vehicle ran with its speed changing within the range of about 10 to 30km/h. Since the scanning frequency of the laser range finder is finite, the distance at which the vehicle moves during the scan of one time could not be exactly disregarded. By using the laser range sensor shown in Table 2, the distance corresponded to about 7cm in the case of 20km/h. Considering that the distance is smaller than the accuracy we intend to estimate, we disregarded this influence in this experiment. Use of a sensor with higher frequency or multiple sensors enabled us to cope in the case of running at higher speed.

4.2. Result and evaluation

4.2.1. Velocity estimation result and evaluation

This time, we segmented each cluster manually and fit 6-dimensinal polynomial function to the cluster segment. Fig.10 shows the aspect of the regression analysis. Fig.11 shows estimated time variation of the velocity of the vehicle and reference curve for evaluation. Evaluation data was obtained from the pitch length of columns of the building (6.0m) and the number of vertical scanning lines included in the pitch shown in Fig.13(a), at each column intervals.

Estimation result approximately agreed with the evaluation data and indicated the effectiveness of our method.

Meanwhile, the maximum error was 8–12% compared with the evaluation data, especially with notable differences at local maximum and local minimum points.

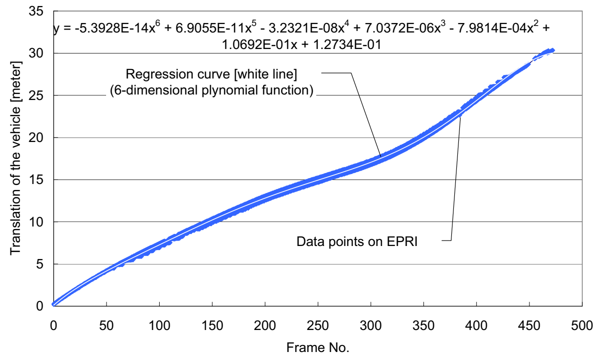


Figure 10: Regression

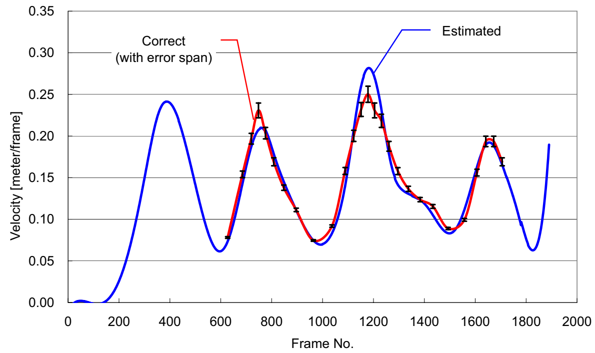


Figure 11: Estimated velocity

4.2.2. 3-D reconstruction result and evaluation

According to the result of estimation, we reconstructed the 3-D geometry of the objective scene by aligning the position of vertical scanning lines. Fig.13 shows the modeling result of the building, before and after the alignment process. As photos in Fig.9 show, columns of the building are actually arranged in equal pitch in the real world. Fig.12 shows the detail of the result. The gap between each scanning line is adjusted according to the vehicle's velocity.

Fig.14 represents positional evaluation result of 3-D reconstruction. Vertical lines of squares drawn in the lower part of the figure represent the positions where the columns of the building should be located. According to this figure, the error becomes approximately 2m at most throughout overall running length of 170m.

4.3. Discussion

4.3.1. Accuracy

The experimental result approximately agrees to the correct answer. Positional error of 2m at most is sufficiently small consiering that accuracy of ordinary GPS is about 10m. Though RTK-GPS provides accuracy of several centimeters in ideal wave condition, such a situation almost never occurs in urban scenes. Moreover, accuracy of this result is expected to good inital value for alignmnent of range data and rough CAD model as described later.

Meanwhile, according to the result of velocity estimation, it includes 8–12% of maximum error.

Regarded causes to the error can be raised as follows:

- Regression by a single polynomial:
  In this experiment, the regression process was carried out by one polynomial per segment. The regression equation was not necesserily a polynomial. It must be examined to use a more suitable equation for vehicle dynamics.

- Completed process in one segment:
  In this experiment, motion of the vehicle was estimated from each segment by a completed process in each segment, and finally they were smoothly combined to estimate whole result. However, the neighbor segment to a certain segment must represent approximately the same velocity. Therefore, the accuracy could be improved by considering inter-segment continuity in the regression step.

- No use of reflectance:
  Reflectance values could not be acquired from the laser range scanner used in this experiment. Using the reflectance edge in addition to the geometric edge in spatio-temporal range image , would enable us to improve the accuracy.

4.3.2. Issues for practical use

In this experiment, we assumed that the running path of the vehicle was straight. When applying our method to the more general case for a curved path, it is necessary to fit curved surfaces instead of curved lines.

Additionally, swinging and variation of the vehicle caused by acceleration or irregularity of the road surface was disregarded in this case; however, such influence can not be inevitable in practical application for city modeling. In our current proposed method, swinging and viration directly affects the quality of vertical scanning lines, where the difference value between the true value becomes proportional to the tangent of roll/pitch/yaw angle.

One of the simplest solutions is to utilize hardware such as a stabilizer; however, use of such devices has a limit for adequate absorption of swinging. Our solutions through software-based approaches are as follows:

- Use of correlation between prior/posterior frames of vertical scanning lines.

- Extraction of road surface and building walls using principal component analysis.

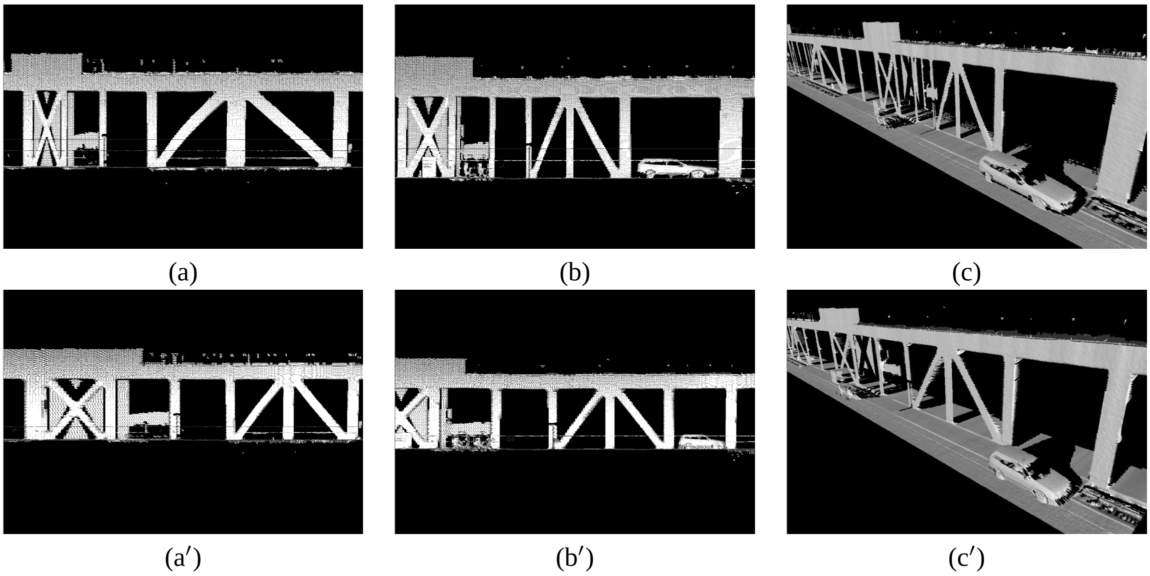


Figure 12: The detail of modeling result, with before(a,b,c) and after(a′,b′,c′) the correction of the vehicle velocity.

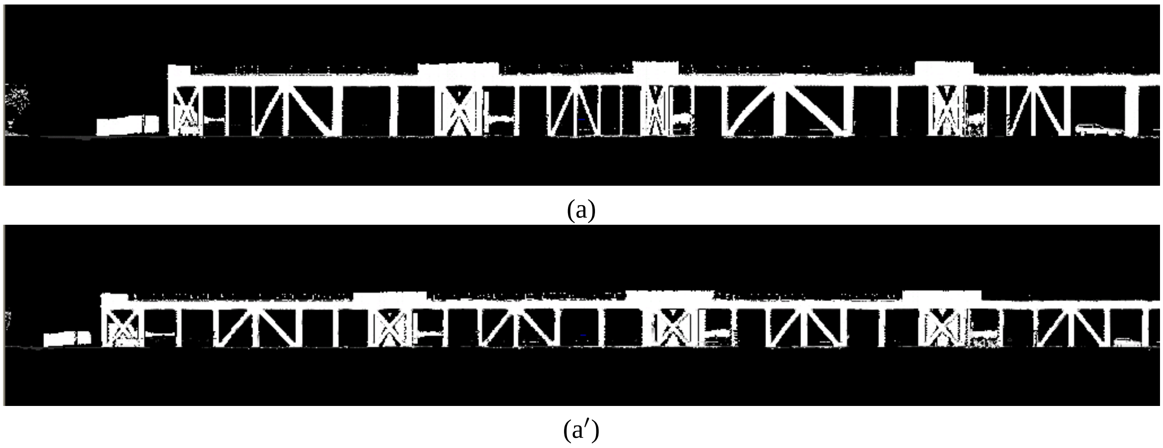


Figure 13: Modeling result: (a)before and (a′)after the correction of the vehicle velocity.

- Use of knowledge that road surface and building walls are right-angled in dominant cases of urban scene.

Moreover, as another approach, we intend to carry out matching between vertical scanning range data and a quite rough 3-D CAD model, which is given by an existing 2-D house map and floor height information, as a framework of alignment between range data with high and low density. This approach is expected to strongly correct the influence of swinging and vibration, in addition to the influence when the running path is not straight. Besides, a digital housemap will enable us to operate global reset to localization result per each intersections Running length in this experiment, 170m, is sufficient regarding our method as a first step in fusing dense range data and rough CAD models.

5. Conclusion

In this paper, we first proposed a novel notion of the epipolar plane range image. The feature of the epipolar plane range image is that it shows both spatial and temporal contiuity simulatneously, and helps in obtaining general tendency of the movement, compared with matching each scanning frame precisely.

And by estimating the velocity of the data acquisition vehicle with this theorem, we have aligned the vertical scanning line which was obtained from another sensor on the vehicle. The vertical scanning lines are correctly aligned according to the vehicle velocity.

All estimation processes have been done without using any external positioning devices such as GPS, which does not have enough accuracy for geometrical alignment in general urban space with low radiowave sensitivity by buildings or skyways.

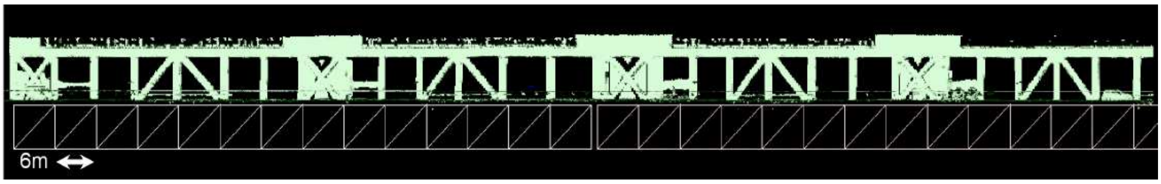


Figure 14: Positional evaluation of 3-D reconstruction. Vertical lines of squares drawn in the lower part represent the positions where the columns of the building should be located.

The future works are raised as follows:

- Accuracy improvement:
  The accuracy of the estimation result will be improved by the approach mentioned in the discussion in the previous section.
- Fully arbitrary motion:
  This time we assumed arbitrary speed and linear motion to the vehicle. By easing this constraint, the spatio-temporal range image becomes a curved surface.
- Further experiments in various environments:
  In these experiments, the scanned objects are mainly ???along??? the column of our building. The experiments in more complicated environments will be necessary to demonstrate the versatility of our method.
- Texture mapping:
  Mounting not only laser range sensors but also cameras will enable us to acquire the textures of urban scenes.
- Calibration of multiple sensors:
  Position and orientation of each sensor will be estimated by analyzing spatio-temporal range image , simultaneously with the motion of the sensor using a parametric alignment technique as [14].

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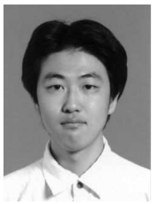

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