# ESTIMATION OF 3D OBJECT POINTS FROM OMNI-DIRECTIONAL IMAGES ACQUIRED BY A ROTATING LINE CAMERA 

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#### Abstract

As various service models integrating 3D GIS with augmented reality are being developed, the demand for indoor spatial data has been increasing rapidly. These data can be effectively derived from indoor omni-directional images, which can be acquired by a stereo rotating line camera. In this study, we thus develop a method to estimate 3D object points from multiple overlapped omni-directional images acquired by the rotating line camera to construct indoor 3D models. Based on the geometry of the rotating line camera, we derive modified collinear equations relating an image point in an omni-directional image with its corresponding object point. Based on these new collinear equations, we estimate the 3D coordinates of object points appearing in at least two images. In the experiment, we acquired two omni-directional images by the rotating line cameras with different rotation radius and applied the proposed method to these data. The result shows that the 3D object points can be obtained within $\pm 15 \mathrm{~cm}$ accuracy. In future, we plan to develop the bundle adjustment for a rotating line camera and estimate the exterior orientation parameters of each omni-directional image as well as the 3D coordinates of object points. The results will then be used further for indoor 3D modeling.


## 1. INTRODUCTION

A great increasing number of service models integrating 3D GIS with augmented reality (AR) leads to the increasing demand for indoor spatial data. Markers indoor augmented reality featured in the Intel Developer Forum is one example for service models integrating 3D GIS with AR (Gadget reviews, 2011). It allows users to access information about space or events by simply clicking on an animation button on an image. Indoor navigation service is also another example. It identifies user's location and guides him to his destination by showing the way through animation on images. Thus, the indoor 3D modeling is required to be generated.

The methods for indoor 3D modeling are generally classified into 3 categories (Biber et al., 2004). The first is where 3D models are generated using a laser scanner. Among these categories, it is the simplest technique but its 3D models lack detailed 3D geometry and textures. The second is where both laser scanner and images are used to generate 3D models. This technique makes 3D geometry through laser scanner and maps textures on 3D model with the images. However, its 3D geometry has less detail than those 3D model generated from images. The third generates 3D model using images. Although this method can generate the detailed 3D geometry, it needs a large number of images which is not so efficient.

To overcome the shortage of images for 3D modeling, Oh and Lee (2010) presented their study on estimating 3D coordinates of object points using omni-directional images of wide coverage. There are various methods to acquire omni-directional images (Huang et al, 2006). Most techniques can be classified into single view or multiple view techniques. The single view technique generates an omnidirectional image from an image acquired with a single view using a fish eye camera or a camera with mirrors. These images have usually heavy distortions, which are difficult to perfectly correct. However, the multiple view technique integrates more than one images acquired with different views using a number of cameras or by moving a camera. These images retain less distortion and higher resolution comparing to those images generated by a single view technique (Silpa-Anan et al., 2005).

Thus, it will be more efficient to create the indoor 3D models using the multiple view omni-directional images. For indoor 3D modeling, it is convenient to acquire omni-directional images by rotating a line camera. The device is lightweight so that it is easy to move and can acquire multiple view omni-directional images. In this paper, we propose a method to estimate 3D object points from omni-directional images acquired by a rotating line camera. In the experiment, we acquired two omni-directional images with different rotation radius and applied the proposed method to these data. We are reporting the intermediate experimental results.

## 2. ESTIMATION OF 3D OBJECT POINTS FROM OMNI-DIRECTIONAL IMAGES

We present a method to estimate 3D object points from multiple overlapped omni-directional images acquired by a rotating line camera for indoor 3D modeling. The proposed method consists of three steps as presented in Figure 1. First, we define the geometry of rotating line camera. Second, we derive new modified collinear equations. Finally, we determine the 3D coordinates of an object point by calculating the intersection of rays from two images

## Define the geometry of a rotating line camera

## Derive new modified collinear equations

## Estimate 3D coordinates of object points

Figure 1. Outline of the estimation method

### 2.1 Geometry of a rotating line camera

In a rotating line camera system, a line camera with $1 \times \mathrm{n}$ pixels is rotated around the rotation center $\left({ }^{0} O_{R}\right)$. A line camera is distant with a radius ( $r$ ) from the rotation center and tilted by an angle ( $\beta$ ), as shown in Figure 2. Here, $P$ is an object point, which can be mapped to an image point $P^{\prime}$ through the rotating line camera. $f$ is the focal length of the line camera. $\alpha$ is the rotation angle measured in counter-clockwise from the positive x -axis $\left({ }^{R} X\right)$ of the rotation coordinate system. ${ }^{R} O_{C}$ is the perspective center of the line camera at the time of exposure.


Figure 2. Geometry of a rotating line camera
$\mathrm{X}-\mathrm{axis}\left({ }^{R} X\right)$ of the rotation coordinate system (RCS) is defined by connecting the rotation center to the starting point of rotation. Y-axis $\left({ }^{R} Y\right.$ ) of RCS is defined by rotating ${ }^{R} X$ counter-clockwise by $90^{\circ}$. Z-axis $\left({ }^{R} Z\right)$ of RCS is the direction of the ceiling. $\mathrm{Y}-\operatorname{axis}\left({ }^{C} Y\right)$ of the camera coordinate system (CCS) is the same as the negative ${ }^{R} Z$. Z -axis $\left({ }^{C} Z\right)$ of CCS is the optical axis which is tilted by an angle $\beta$ from the line connecting the rotation center to the camera position. X -axis $\left({ }^{C} X\right)$ of CCS is defined by rotating ${ }^{C} Y$ clockwise by $90^{\circ}$.

### 2.2 Collinear equations for a rotating line camera

The collinear equations describe the relationships between an object point and its corresponding image point projected by the rotation line camera. Their derivation mainly includes three steps, (1) the coordinate
transformation of an object point expressed in the object coordinate system (OCS) into the camera coordinate system (CCS), (2) the perspective projection of the transformed object point into an image point, and (3) the coordinate transformation of the projected image point expressed in the camera coordinate system (CCS) into the image coordinate systems (ICS).
2.2.1 Coordinate transformation from OCS and CCS: An object point expressed in the OCS ( ${ }^{\mathbf{0}} \mathbf{P}$ ) is transformed into the rotation coordinate system $\left({ }^{\mathbf{R}} \mathbf{P}\right)$. ${ }^{\mathbf{R}} \mathbf{P}$ is then transformed into the camera coordinate system $\left({ }^{\mathbf{C}} \mathbf{P}\right)$. The equation for coordinate transformation is expressed as

$$
\begin{equation*}
{ }^{C} P={ }^{C} R_{R}\left({ }^{R} P-{ }^{R} O_{C}\right)={ }^{C} R_{R}\left\{{ }^{R} R_{O}\left({ }^{C} P-{ }^{o} O_{R}\right)-{ }^{R} O_{C}\right\} \tag{1}
\end{equation*}
$$

where ${ }^{R} R_{O}$ is the rotation matrix for the transformation from OCS into RCS.

$$
{ }^{R} R_{O}=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & \cos \omega & -\sin \omega \\
0 & \sin \omega & \cos \omega
\end{array}\right]\left[\begin{array}{ccc}
\cos \varphi & 0 & \sin \varphi \\
0 & 1 & 0 \\
-\sin \varphi & 0 & \cos \varphi
\end{array}\right]\left[\begin{array}{ccc}
\cos \kappa & -\sin \kappa & 0 \\
\sin \kappa & \cos \kappa & 0 \\
0 & 0 & 1
\end{array}\right] .
$$

${ }^{R} O_{C}$ is the perspective center of the line camera expressed in RCS where the image is captured, expressed as

$$
{ }^{R} O_{C}=\left[\begin{array}{c}
r \cos \alpha \\
r \sin \alpha \\
0
\end{array}\right] .
$$

${ }^{C} R_{R}$ is the rotation matrix for the transformation from RCS into CCS, expressed as

$$
{ }^{c} R_{R}=\left[\begin{array}{ccc}
0 & 1 & 0 \\
0 & 0 & -1 \\
1 & 0 & 0
\end{array}\right]\left[\begin{array}{ccc}
\cos (\alpha+\beta) & -\sin (\alpha+\beta) & 0 \\
\sin (\alpha+\beta) & \cos (\alpha+\beta) & 0 \\
0 & 0 & 1
\end{array}\right]
$$

and $\alpha$ is the rotation angle derived as

$$
\alpha=\operatorname{atan} 2\left({ }^{R} Y,{ }^{R} X\right)+\sin ^{-1} \frac{r \sin (\pi-\beta)}{\sqrt{R_{X^{2}}+Y^{2}}}-\beta .
$$

2.2.2 Projection of object point to image point: An object point expressed in CCS (P) is projected into image point $\left(\mathbf{P}^{\prime}\right)$ as shown in Figure 3. The projection can be formulated as (2).

$$
\begin{equation*}
P^{\prime}=\frac{1}{\lambda} P \tag{2}
\end{equation*}
$$

where $\lambda$ is an scale factor $\lambda=\frac{c_{Z}}{f}$.


Figure 3. Projection of an object point to the corresponding image point
2.2.3 Coordinate transformation from CCS and ICS: An image point expressed in CCS should be finally transformed into ICS. Actually, the transformed coordinates in ICS are the column and row indexes $(i, j)$ in an image. This transformation can be expressed as

$$
\left.\left[\begin{array}{l}
i  \tag{3}\\
j
\end{array}\right]=\left[\begin{array}{c}
\frac{\alpha+\beta}{\mu_{\alpha}} \\
c_{Y^{\prime}} \\
\mu_{j}
\end{array}\right] \frac{n}{2}\right]
$$

where $\boldsymbol{n}$ is the number of pixels of a line camera; and $\boldsymbol{\mu}_{\boldsymbol{\alpha}}$ and $\boldsymbol{\mu}_{\mathbf{j}}$ are the rotation angle and the height of each pixel, respectively.

### 2.3 Calculation of 3D object point coordinates

An object point can be determined from the corresponding image points appearing in at least two images. From each image point, we can determine a straight line starting from the perspective center through the image point toward the object point. The object point corresponding to the image point should exist on this straight line. If we have a set of straight lines derived from a set of the image points, their intersection must be the object point corresponding to the set of the image points.

## 3. EXPERIMENTAL RESULTS

In the experiment, we acquired two omni-directional images with different rotation radius. We applied the proposed method to these data to determine a set of object points, which are then verified with the true data.

### 3.1 Data acquisition

3.1.1 A rotating line camera: In order to acquire omni-directional images, we set up a rotating line camera as shown in Figure 4. A line camera can capture, at once, a one-dimensional image of size 1x4000 pixels according to the Z-axis of the rotation coordinate system. Rotating the camera in clockwise direction around the rotation center can produce a two dimensional omni-directional image. The line camera in used has 15 mm focal length and its pixel size is $10 \mu \mathrm{~m} \times 10 \mu \mathrm{~m}$.


Figure 4. A rotating line camera
3.1.2 Omni-directional images: The experimental area is about $3.22 \mathrm{~m} \times 6.45 \mathrm{~m} \times 2.50 \mathrm{~m}$. We acquired two omni-directional images with two different rotation radius, 0 and 18 cm , respectively. The dimension of the captured images is $8000 \times 4000$ and the field of view covered by each pixel is $0.045^{\circ}$. Figure 5 and 6 show the acquired stereo omni-directional images.


Figure 5. Image 1 with a rotation radius of 0 cm


Figure 6. Image 2 with a rotation radius of 18 cm

### 3.2 Accuracy verification

We measured 14 image points as shown in Figure 5 and 6 and estimated their corresponding object points. For verification, we calculated the distance between two points and compared the estimated distance with real measured values. The experimental result shows that the 3D object points are obtained with $\pm 12.4 \mathrm{~cm}$ accuracy.

Table 1. 3D coordinates of object points and comparison between the estimated and measured distances

| $\begin{gathered} \text { Line } \\ \text { ID } \end{gathered}$ | Point ID | 3D coordinates(m) |  |  | True value of line(m) | Estimated value of line (m) | Error(m) |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | X | Y | Z |  |  |  |
| L1 | 1 | 0.0041 | 1.4679 | -0.2382 | 0.7000 | 0.6872 | -0.0128 |
|  | 2 | -0.6562 | 1.6574 | -0.2210 |  |  |  |
| L2 | 3 | -0.7022 | 1.6619 | -0.5618 | 0.7000 | 0.6752 | -0.0248 |
|  | 4 | -1.3548 | 1.8349 | -0.5528 |  |  |  |
| L3 | 5 | -2.1985 | 1.3255 | 0.4482 | 2.0500 | 1.9318 | -0.1182 |
|  | 6 | -2.3020 | 1.3751 | -1.4801 |  |  |  |


| L4 | 7 | -1.8725 | -0.4534 | 0.2253 | 0.7500 | 0.7389 | -0.0111 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | 8 | -1.1585 | -0.6431 | 0.2141 |  |  |  |
| L5 | 9 | -1.1325 | -0.6597 | -0.1363 | 0.7500 | 0.7380 | -0.0120 |
|  | 10 | -0.4201 | -0.8519 | -0.1497 |  |  |  |
| L6 | 11 | -0.3916 | -0.8728 | -0.4689 | 0.7500 | 0.7382 | -0.0118 |
|  | 12 | 0.3193 | -1.0701 | -0.4920 |  |  |  |
| L7 | 13 | 0.3540 | -1.0873 | -0.7569 | 0.7500 | 0.7335 | -0.0165 |
|  | 14 | 1.0621 | -1.2691 | -0.8165 |  |  |  |

## 4. CONCLUSIONS

In this paper, we proposed an accurate method to estimate 3D coordinates of the object points for indoor 3D modeling. In the experiment, we acquired two omni-directional images using a rotating line camera and employed our proposed method to determine the object points. The result shows that the 3D object points can be obtained with $\pm 12.4 \mathrm{~cm}$ accuracy. In future, we plan to develop the bundle adjustment for a rotating line camera and estimate the exterior orientation parameters of each omni-directional images, the tilted camera angle, the rotation radius and the 3D coordinates of object points. The proposed estimation method must be useful to generate the detailed indoor 3D model.

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