

# Environment Measurement based on Structure from Motion with Feature Flow Model Using Omni-Directional Camera

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*Map information is important for path planning and self-localization when mobile robots execute autonomous tasks. In unknown environments, mobile robots should generate their own environmental maps. Then, we propose a method for 3D environment modeling by a mobile robot. For environmental measurement, we use a single omni-directional camera. This paper proposes a new estimation method of camera movement for improvement in measurement robustness and accuracy. The method takes advantage of a wide field of view of an omni-directional camera. Experimental results showed the effectiveness of the proposed method.*

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## NOMENCLATURE

$a, b, c$  = parameter of hyperboloid mirror  
 $f$  = image distance  
 $\mathbf{r}$  = ray vector  
 $\mathbf{R}$  = Rotation matrix  
 $\mathbf{t}$  = translation vector  
 $\mathbf{g}$  = error vector  
 $\mathbf{c}$  = camera position

## 1. Introduction

Map information is important for path planning and self-localization when mobile robots accomplish autonomous tasks. Therefore, in unknown environment, mobile robots should construct an environment map by themselves.

3D measurement using image data makes it possible to generate map information [1]. However, an image acquired by a conventional camera has a limited field of view [2]. To solve this problem, such cameras with a wide field of view have been invented as a fisheye camera [3], an omni-directional camera [4] [5] and so on. Taking account of installation on a mobile robot, an omni-directional camera is suitable because it can get a surrounding view image at once. Gluckman and Nayer showed that an omni-directional camera is effective in measurement and recognition in environment [6].

A stereo vision method using two omni-directional cameras is proposed [7]. The measurement accuracy by stereo vision depends on the baseline length. The longer the baseline length is, the better the accuracy is. However, the measurement accuracy of the above method is limited because the baseline length cannot be longer than the robot size. A motion stereo method using stereo pair images which are taken with a single camera at different observation points is equivalent to binocular stereo vision. This method can make the baseline length longer without restriction of the robot size [8].

Therefore, the method can measure with higher accuracy than binocular stereo method.

Measurement accuracy can be expected to be higher by using a sensor fusion method using laser [9], GPS [10] or sonar [11] with an omni-directional camera. However, there are some problems that measurement objects and situations are limited and that complexity of calibration process for each device increases.

Therefore, we use a single omni-directional camera for environmental measurement. The structure from motion (SFM) is a kind of motion stereo method. The SFM method estimates camera movement (the relative relations of camera positions and orientations), and then measures objects in images. We have already proposed a measurement method based on the SFM [12]. Our method extracts and tracks feature points to get corresponding points in an omni-directional image sequence. By using position relations of the corresponding points, the method estimates camera movement and measures its environment. A triangular mesh is generated from measurement data. By texture-mapping, a 3D environment model is constructed.

Estimation of precise camera movement is important for improvement of the accuracy in measurement by the SFM. Then, we propose a method which estimates precise camera movement by taking advantage of an entire field of view of omni-directional camera.

## 2. Outline

A mobile robot executes 3D measurement and modeling by using an omni-directional camera (Fig.1). The mobile robot acquires an omni-directional image sequence during its locomotion.

The process of our method is shown in Fig.2. It extracts and tracks feature points to get corresponding points in an omni-directional image sequence. By using the positions of corresponding points in two images taken at different observation points, we estimate camera movement with a feature flow model we propose. 3D coordinates of object points are calculated by triangulation with

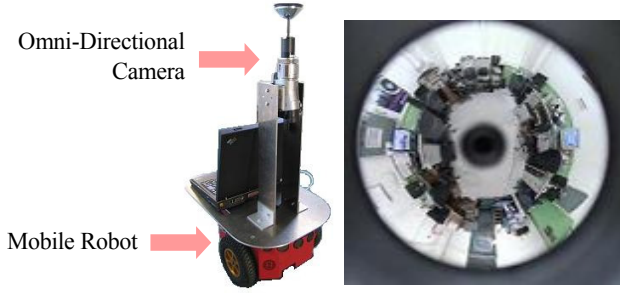


Fig.1 Mobile Robot with Omni-Directional Camera

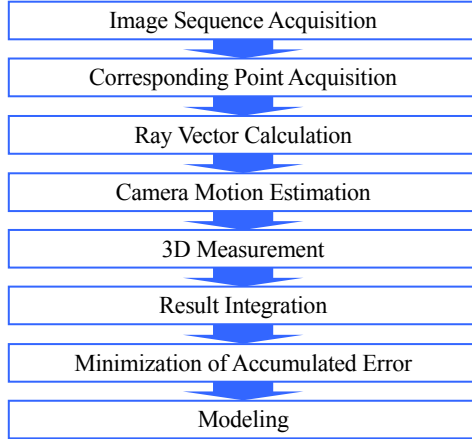


Fig.2 Proposed Flow

camera movement and image coordinates of feature points. In order to decrease accumulated errors, we minimize errors in feature point coordinates and camera movement by bundle adjustment. Finally, the individual measurement data of feature points are integrated as one 3D measurement data.

### 3 Environment Measurement

#### 3.1 Corresponding Point Acquisition

For getting correspondent points between images in the omni-directional image sequence, the method extracts feature points in the initial image and then tracks them along the sequence. In our method, we use Lucas Kanade tracker algorithm with image pyramid representation [13] (Fig.3). These points are regarded as corresponding points between two images taken before and after the robot movement.

#### 3.2 Ray Vector Calculation

We define a unit vector originating from the center of projection to an object point in 3D space as a ray vector  $\mathbf{r} = [x, y, z]^T$ , where  $T$  stands for transposition of vector or matrix. An omni-directional camera we use has a hyperboloid mirror in front of the lens of a conventional camera. Therefore, as shown in Fig.4, ray vector  $\mathbf{r}$  is directed from the focus of the hyperboloid mirror to the reflection point of the ray on the mirror surface.

Ray vector  $\mathbf{r}$  is calculated from image coordinates  $(u, v)$  of the feature point using (1), (2).

$$\mathbf{r} = \begin{bmatrix} su \\ sv \\ sf - 2c \end{bmatrix} \quad (1)$$

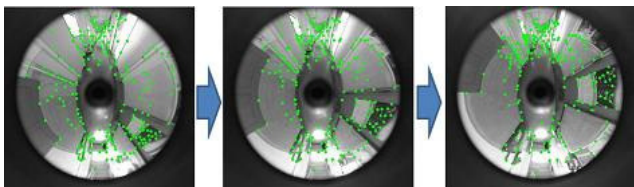


Fig.3 Feature Point Extraction and Tracking

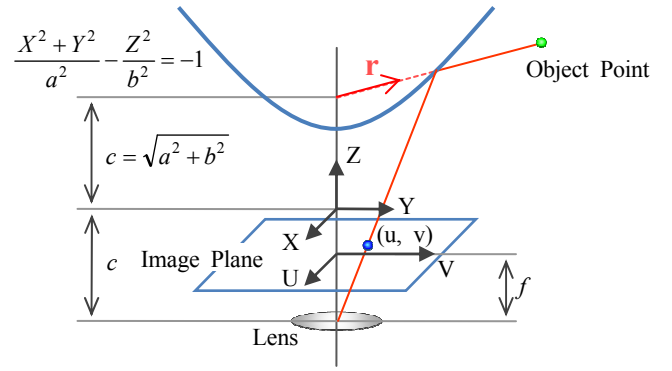


Fig.4 Calculation of Ray Vector

$$s = \frac{a^2 \left( f\sqrt{a^2 + b^2} + b\sqrt{u^2 + v^2 + f^2} \right)}{a^2 f^2 - b^2 (u^2 + v^2)} \quad (2)$$

In these equations,  $a$ ,  $b$  and  $c$  are the hyperboloid parameters and  $f$  is the image distance which is the distance between a center of a lens and the image plane.

### 3.3 Camera Movement Estimation

#### 3.3.1 Feature Point Movement

In the case of using a conventional camera, its field of view is restricted to a narrow area around the optical axis. For this reason, there may be not much difference in feature point's movement in images between translation and rotation of the camera (Fig.5(a)). Therefore, in that case, it is difficult to estimate camera movement by analyzing movement of feature points in images.

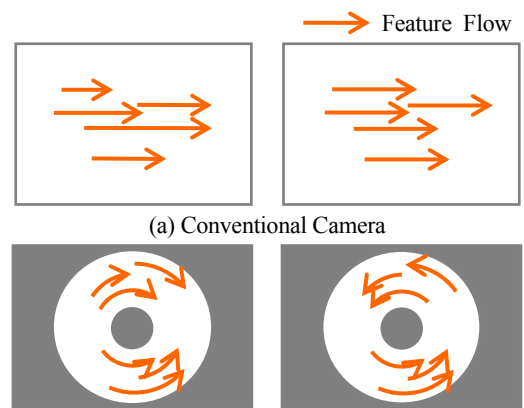
On the other hand, in the case of using omni-directional camera which has 360 degree field of view, we can specifically discriminate between translation and rotation of the camera by analyzing movement of feature points in any cases (Fig.5(b)).

Then, we propose an estimation method of camera movement by utilizing a difference in feature point movement between camera rotation and translation.

#### 3.3.2 Feature Flow Model

Our method defines a unit sphere for camera movement estimation. The center of this unit sphere represents the starting points of each ray vector and a camera translation vector. These vectors are unit vectors. Rotation axes of camera movement pass through the center of the unit sphere. A relation between ray vectors  $\mathbf{r}_1$ ,  $\mathbf{r}_2$ , camera translation vector  $\mathbf{t}$ , camera rotation axis and angle displacements is described below.

In the case of camera translation, a translation vector is in a plane which consists of two ray vectors  $\mathbf{r}_1$ ,  $\mathbf{r}_2$  acquired before and after camera movement. Therefore, a normal vector of this plane given by (3) is orthogonal to a translation vector (Fig.6(a)), and this leads to (4).



(b) Omni-Directional Camera

Fig.5 Feature Flow

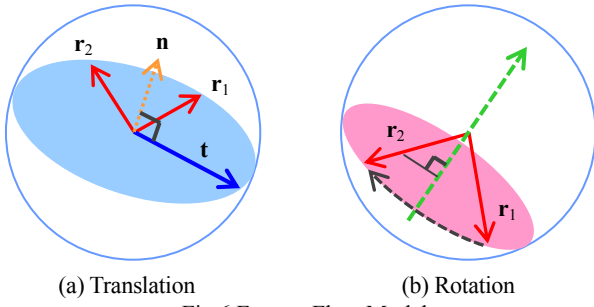


Fig.6 Feature Flow Model

$$\mathbf{n} = \mathbf{r}_{11} \times \mathbf{r}_{12} \quad (3)$$

$$\mathbf{n} \cdot \mathbf{t} = 0 \quad (4)$$

In the case of camera rotation, ray vector's displacements are constant angle displacement in a plane which is orthogonal to a rotation axis. Here, a relation between two ray vectors  $\mathbf{r}_{R1}$  and  $\mathbf{r}_{R2}$  is described by (5) using a rotation matrix (Fig.6(b)).

$$\mathbf{r}_{R1} = \mathbf{R}^{-1} \mathbf{r}_{R2} \quad (5)$$

In the case of both translation and rotation, a relation between two ray vectors  $\mathbf{r}_1$  and  $\mathbf{r}_2$  acquired before and after camera movement can be described by the combination of these displacements. In this unit sphere, these displacements are independent of each other. Therefore, we can deal with this case as well as the case of translation by removing rotation displacements from the combination of two displacements.

Then, we can describe camera movement by following (6).

$$(\mathbf{r}_1 \times \mathbf{R}^{-1} \mathbf{r}_2) \cdot \mathbf{t} = 0 \quad (6)$$

Here, there are two solutions for the translation vector and the rotation matrix which satisfy (6), respectively. In the translation vector, one of the solutions is the correct translation vector  $\mathbf{t}$  which describes camera movement. The other solution is the vector in the reverse direction of the correct translation vector (reverse translation vector). In the rotation matrix, one of the solutions is the correct rotation matrix  $\mathbf{R}$  which describes camera movement. The other solution is the rotation matrix which rotates 180 degrees from the correct rotation matrix around the translation vector. Then, we should determine which is correct between these two solutions, respectively.

Our method solves the problem by applying two constraint conditions. One of the constraint conditions is that displacements of ray vectors are in the direction from the end point of the correct translation vector (positive pole) to the end point of the reverse translation vector (negative pole). This constraint condition decides the direction of the correct translation vector. The other constraint condition is that displacements of ray vectors do not cross over the positive pole or the negative pole. This constraint condition decides the correct rotation matrix.

When the rotation matrix and the translation vector satisfy these constraint conditions, ray vectors satisfy (7) geometrically (Fig.7).

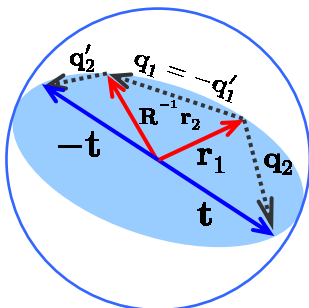
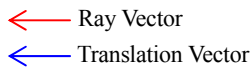


Fig.7 Constraint Condition

$$\mathbf{q}_1 \cdot \mathbf{q}_2 < 0 \quad \cap \quad \mathbf{q}'_1 \cdot \mathbf{q}'_2 < 0 \quad (7)$$

where

$$\mathbf{q}_1 = \mathbf{R}^{-1} \mathbf{r}_2 - \mathbf{r}_1, \quad \mathbf{q}_2 = \mathbf{t} - \mathbf{r}_1, \quad \mathbf{q}'_1 = -\mathbf{q}_1, \quad \mathbf{q}'_2 = -\mathbf{t} - \mathbf{R}^{-1} \mathbf{r}_2.$$

This equation means that both the angle between vector  $\mathbf{q}_1$  and vector  $\mathbf{q}_2$  and the angle between vector  $\mathbf{q}'_1$  and vector  $\mathbf{q}'_2$  are obtuse.

Our method estimates the rotation matrix and the translation vector which satisfy both (6) and (7) for all the pairs of ray vectors  $\mathbf{r}_{1,i}$  and  $\mathbf{r}_{2,i}$  by minimizing the amount  $E$  given by (8) and (9).

$$e_i = \begin{cases} |(\mathbf{r}_1 \times \mathbf{R}^{-1} \mathbf{r}_2) \cdot \mathbf{t}| & \text{if (7) is satisfied} \\ 1 & \text{else} \end{cases} \quad (8)$$

$$E = \sum_i e_i \quad (9)$$

This method we propose is based on a model which has uniform flow of ray vector's displacements on a unit sphere. Here, we call the model of the unit sphere a feature flow model (FFM).

### 3.4 3D Measurement

3D coordinates of an object point which is projected as a feature point in the image are given based on triangulation with two cameras set in the geometrical relation given by rotation matrix  $\mathbf{R}_m$  and translation vector  $\mathbf{t}_m$ , where  $m$  is the number of measurement. We calculate 3D coordinates of  $\mathbf{p}_{m,i}$  ( $i$ -th feature point) by using  $\mathbf{R}_m$  and  $\mathbf{t}_m$  (Fig.8).

The accuracy of measurement is lower when an object point lies close to the baseline direction or it lies far from the camera. Therefore, the measurement data is a mixture of high and low accuracy. Here, by taking the differentiation of measurement result  $\mathbf{p}_{m,i}$  by the image coordinates of the two feature points  $[u_{1,m,i}, v_{1,m,i}]^T$  and  $[u_{2,m,i}, v_{2,m,i}]^T$  as the estimate of the measurement accuracy, we select measurement results satisfying (10) and (11), where  $h$  is a threshold.

$$\mathbf{g}_{m,i} = \left| \frac{\partial \mathbf{p}_{m,i}}{\partial u_{1,m,i}} \right| + \left| \frac{\partial \mathbf{p}_{m,i}}{\partial v_{1,m,i}} \right| + \left| \frac{\partial \mathbf{p}_{m,i}}{\partial u_{2,m,i}} \right| + \left| \frac{\partial \mathbf{p}_{m,i}}{\partial v_{2,m,i}} \right| \quad (10)$$

$$\|\mathbf{g}_{m,i}\| < h \quad (11)$$

### 3.5 Result Integration

By the above procedure, we get individual measurement results and the geometrical relations of observation points by using pairs of stereo images that are selected in the image sequence. In order to unite these measurement results, we solve the problem of scale ambiguity among individual measurements by scale matching [14]. However, there is a mismatching of the measurement results because the errors included in feature points are different between each observation point.

Therefore, after scale matching, there are more than two measurement results which show the same object point. We integrate these measurement results into one object point by voting to voxels which are divided in 3D space. The 3D coordinates of the object point are the coordinates of the voxel which has the largest value.

### 3.6 Minimization of Accumulated Error

The camera movement estimated in section 3.4 includes some errors. These measurement errors are accumulated after result integration (section 3.5). For the solution of the problem, Bundle adjustment is known as a minimization method of accumulated errors [15].

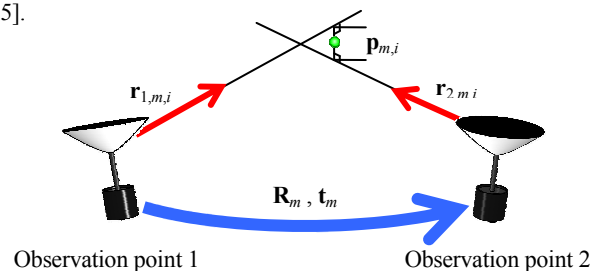


Fig.8 Calculation of 3D Coordinates

To decrease accumulated errors, our method minimizes the errors between the ray vectors calculated by (1) and the vectors whose direction is given by the 3D coordinates of the feature point (reprojected vector). The reprojected vector is calculated by (12) and (13).

$$\mathbf{r}'_{1,m,i} = \mathbf{R}_{m-1}(\mathbf{p}_i - \mathbf{c}_{m-1}) \quad (12)$$

$$\mathbf{r}'_{2,m,i} = \mathbf{R}_m(\mathbf{p}_i - \mathbf{c}_m) \quad (13)$$

Here,  $\mathbf{c}_m$  is the camera locations at the observation point  $m$ .  $\mathbf{R}_m$  is the rotation matrix at the observation point  $m$ . We define the accumulated error as follows.

$$\varepsilon_m = \sum_i w_{m,i} \left( \|\mathbf{r}_{1,m,i} - \mathbf{r}'_{1,m,i}\|^2 + \|\mathbf{r}_{2,m,i} - \mathbf{r}'_{2,m,i}\|^2 \right) \quad (14)$$

where  $\varepsilon_m$  is the accumulated errors in  $m$ -th frame,  $w_{m,i}$  is the weight factor which evaluates the measurement error by using the norm of the vector  $\mathbf{g}_{m,i}$  calculated by (10) for  $i$ -th feature point,  $\mathbf{r}_{m,i}$  is the ray vector,  $\mathbf{r}'_{m,i}$  is the reprojected vector. The weight factor  $w_{m,i}$  is calculated by (15).

$$w_{m,i} = \frac{1}{\mathbf{g}_{m,i}} \quad (15)$$

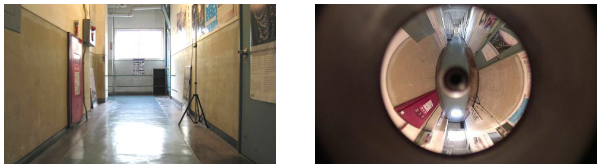
### 3.7 Modeling

A triangular mesh is generated from integrated measurement data by using 3D Delaunay triangulation. But, the Delaunay triangulation generates a triangular mesh which contradicts a physical shape because the triangular mesh does not consider the shape of the measurement object. Therefore, we apply the triangular optimization method [16] to the triangular mesh. The method adapts the triangular mesh to the physical shape by detecting a texture distortion. By texture mapping to the triangular mesh, a 3D environment model is constructed.

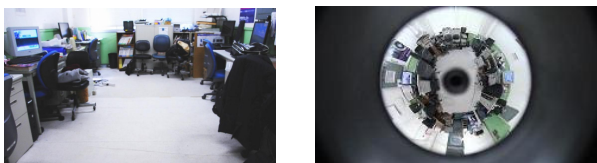
## 4 Experiments

We construct a model of an actual environment by measurement method based on a FFM by using a mobile robot which equips an omni-directional camera. In the experiment we measured two environments (Fig.9 (a) a passageway including an L-shape corner, (b) a room). We acquired an image sequence (10 fps) of these environments by using a mobile robot. The robot ran with 100 mm/s. The image size is  $1920 \times 1080$  pixels.

Figure 10 shows the bird's-eye view and the top view of combined measurement result of the passageway and the room. The marks in these results show the 3D coordinates of camera's trajectory and corresponding points. In these figures, the color change shows the change of the observation point. The blue marks show the result measured at the initial observation point. The red marks show the result measured at the end of observation point. The result of the passageway shows that our method can measure the L-shape corner. But we cannot measure the room in detail, because the measurement result of the room is sparse. It is our assignment.



(a) Passageway (left: Actual Image, right: Input Image)



(b) Room (left: Actual Image, right: Input Image)

Fig.9 Experimental Environment

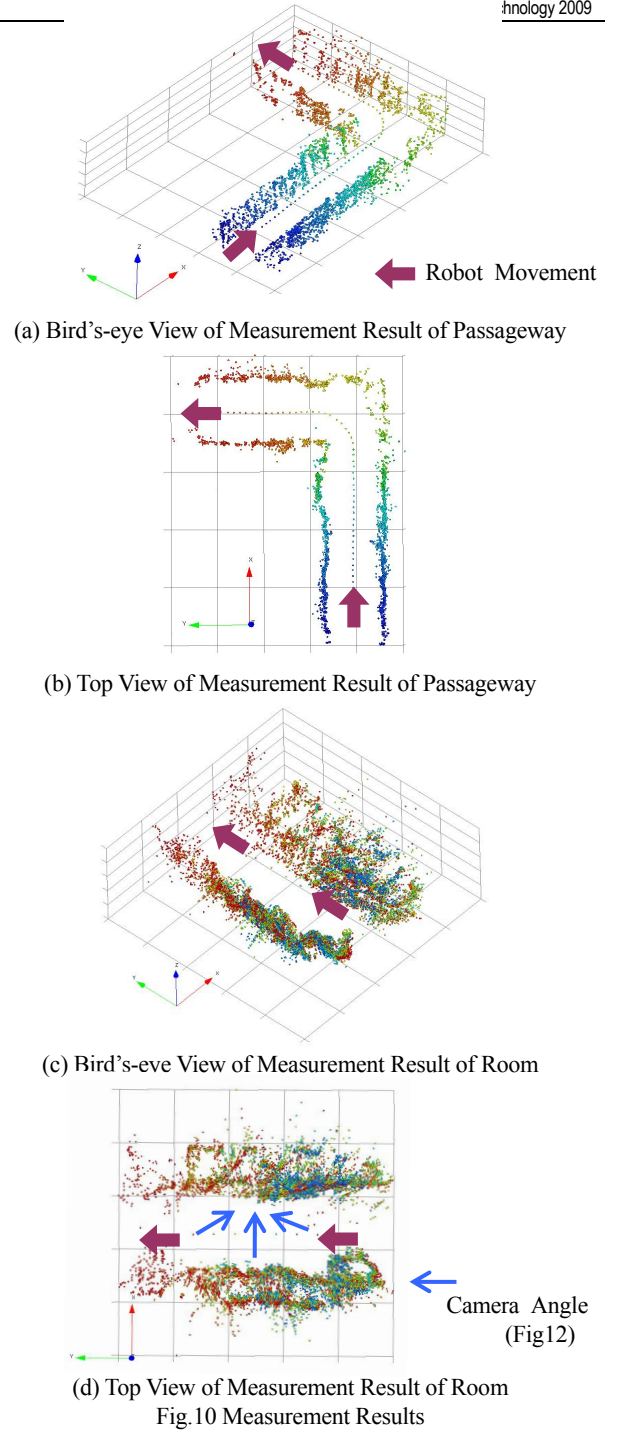


Fig.10 Measurement Results

Figures 11 and 12 show the 3D environment models of the passageway and the room. Figure 11 shows that our proposed method can construct a model which has the shape of the passageway. But the room model has much texture distortion because the density of the measurement result is not enough and the result includes imprecise measurement points.

## 5 Conclusions

In this paper, we propose a method which estimates camera movement precisely by taking advantage of the wide field of view of an omni-directional camera. Experimental results show the effectiveness of our proposed method.

As future works, we should make the following improvements. For measurement accuracy, the baseline length should be optimized by considering the measurement result at each observation point. For appearance of the environment model, we should estimate the shape of measurement objects in the environment from the relation between the measurement result and the texture appearance at each observation point.



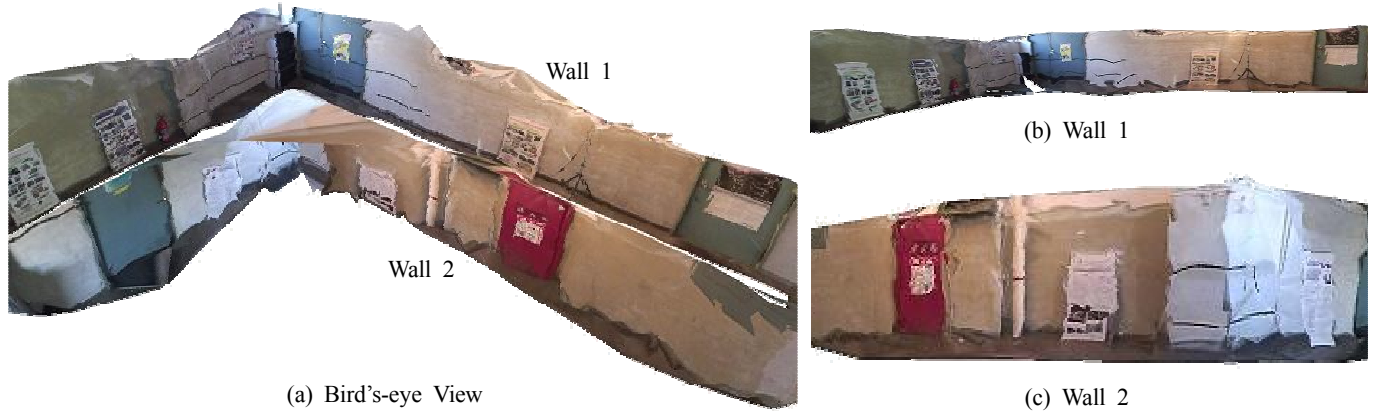
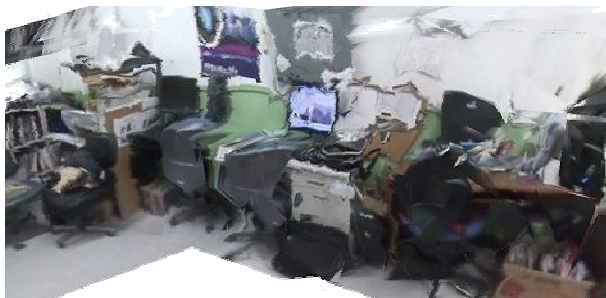


Fig.11 3D Environment Model of Passageway



(a) Front View



(b) Right View



(c) Left View

Fig.12 3D Environment Model of Room

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