Matching Evaluation of 2D Laser Scan Points using Observed Probability in Unstable Measurement Environment

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***Abstract*— In the real environment such as urban areas sidewalk, the laser scanner measurement is unstable due to various noise such as moving object. The unstable measurement makes difficult for mobile robot localization. While, the stable measured object is effective as landmark. And, it is expect that around the stable measured object, the scan points is frequently obtained greater than unstable measurement with multiple scans. Hence, the observed probability of scan point allows to extract the features of stable measured object and decrease the influence of unstable measurement. This paper presents the calculation of the observed probability of laser scan point for mobile robot localization. The observed probability is statistically obtained from multiple scans when obtained in a priori. Using this localization method, our robot moves completely on the pedestrian environment of about 1.2km at Tsukuba Challenge 2011.**

I. Introduction

Localization is an important function for mobile robots. Scan matching using laser scanner is widely used for localization methods. Scan matching estimate robot position by measuring the correlation of current scan with reference scan and arranging for the correlation to be greater. For autonomous navigation, usually, the reference scan is a priori scans in the environment or made from these scans. In scan matching scheme, hence, it is assumed that current and reference scan are similar. In the real environment such as urban areas sidewalk, however, laser scanner measurement is unstable due to moving objects, change of scanning area by tilt or vibration of robot, and so on. By unstable measurement, miss correspondence between reference scan and current scan occurs, and the correlation

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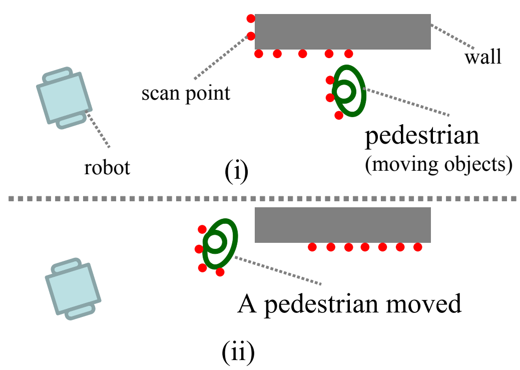


Fig. 1. Unstable measurement by moving object: The scan data change by the postion of moving object.

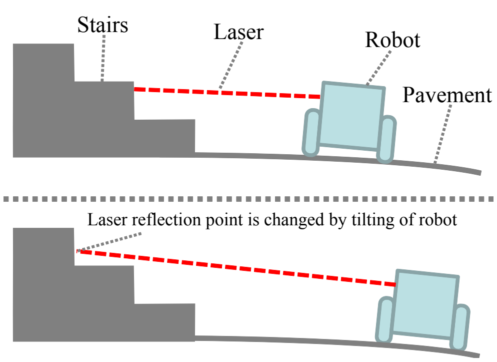
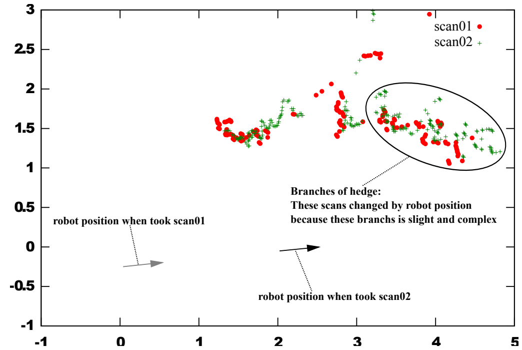


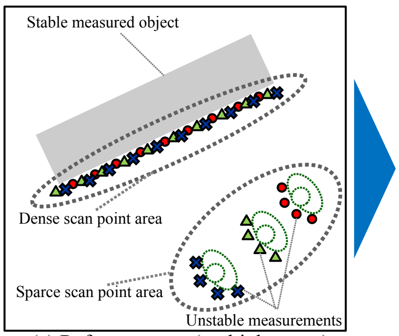
Fig. 2. Unstable measurement by change of scan area: The measured object change due to robot tilt by slight slope of the pavement.

(a) Complex object: Branches of hedge

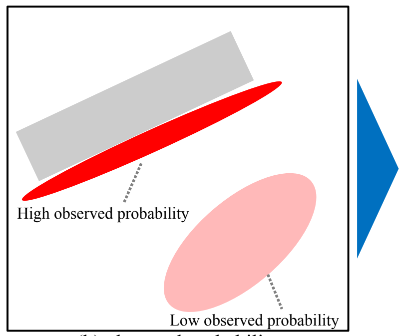


(b) Unstable mesurement of complex object

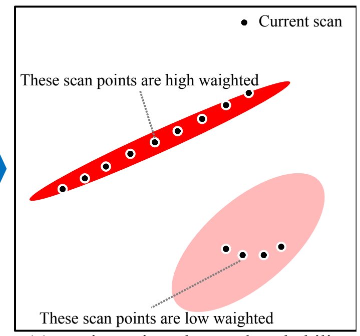
Fig. 3. Unstable measurement of complex object



(a) Reference scan (multiple scans)



(b) observed probability



(c) scoring using observed probability

Fig. 4. The evaluation of current scan using the observed probability: (a) shows the multiple scans as reference scan. The wall is stably measured and the scan points around the wall is dense. While the walker is unstably and these scan points is sparce. (b) shows the observed probability of scan points that obtained from scans of (a). (c) shows the scoring how much the current scan match to the reference. The scan points around high observed probability area is waighted because scan points expect to observed around high observed probability area.

of current scan and reference scan is reduced. As a consequence, unstable measurement makes difficult to estimate robot position.

For stable measured objects (that is observed at approximately the fixed position) current scan is able to correspond easily reference scan. With multiple scans, the density of scan points around stable measured objects is greater than the density of unstable measurement area. In the dense scan points area, it is expected that a scan point observed with high probability. The observed probability of scan points allows to extract effective features for localization and decrease the influence of unstable measurement data for mobile robot localization. This paper describes to calculate the observed probability from the reference scans and the score of scan matching using the observed probability.

II. Approach

In the real environment such as urban areas sidewalk, the laser scanner measurement is unstable and it makes robot localization difficult. The cause of unstable measurement are various; moving objects such as walkers will change its position with time (Fig.1), the laser reflection point will be changed by tilting or vibration of robot (Fig.2), the scan of complex objects is unstable measured (Fig.3), and so on. Unstable measurement is difficult to be solved due to variety of cause. Usually undesired data is deleted manually from reference scan for avoiding miss correspondence. However, manual deletion of undesired data is the burden and the person is required to have enough knowledge about the environment.

The feature-based scan matching [1],[2] allows to extract reliable features for localization. Because thie method extracts the specific feature such as line from both reference and current scan, it is efficient method for noisy and unstable measurement. However, the feature-based scan matching needs the specific feature, and it is difficult to be applied to some outdoor environment having fe specific features.

Many approaches for range sensor locaziation consider the occupancy or free area. These approach is robust for unstable measurement by moving object [4][5][6]. However, the cause of unstable measurement is not only moving objects. For example, the occupancy area and free area become less apparent due to the reflection point change by the slight slope of the pavement like shown in Fig.2.

The likelihood that the current scan is observed at the robot position can be used to estimate the robot position. This paper presents a method to caluculate statiscally the observed probability of scan points as the score from multiple scans obtained in a priori. Shown in Fig.4-(a), with multiple scans, scan points is dense around stable measured objects. While scan points of unstable measurement is sperce and low observed probability. The observed probability at dense scan point area will be greater than it at sparce area (Fig.4-(b)). Finally the observed probability allows to weight to the feature of stable measured objects and reduce the influence of unstable measurements.

III. SCORING ROBOT POSITION USING OBSERVED PROBABILITY

One of the localization method using laser scanner is to evaluate the robot position by the likelihood of current scan and to optimize the robot position evaluation. In this section, the scoring method using the observed probability obtained from reference scans M is presented. To obtain reference scans, the robot moves manually on the environment in a priori, and gathers self position and 2D laser scanner data. By associating the robot position and laser scanner data, the scan data around the enrivonment is obtained. Here, the current scan is described $Z = \mathbf{z}_1, \mathbf{z}_2, ...\mathbf{z}_m$ and a current scan point poition is $\mathbf{z} = (x_z, y_z)$. The robot position on the reference scan coordinate is described $\mathbf{p} = (x_p, y_p, \theta_p)^T$ and the i'th current scan point on the reference scan coordinate $\mathbf{z}'_i$ is

$$\mathbf{z}'_i = \begin{pmatrix} cos(\theta_p) & -sin(\theta_p) \\ sin(\theta_p) & cos(\theta_p) \end{pmatrix} \mathbf{z}_i + \begin{pmatrix} x_p \\ y_p \end{pmatrix} \quad (1)$$

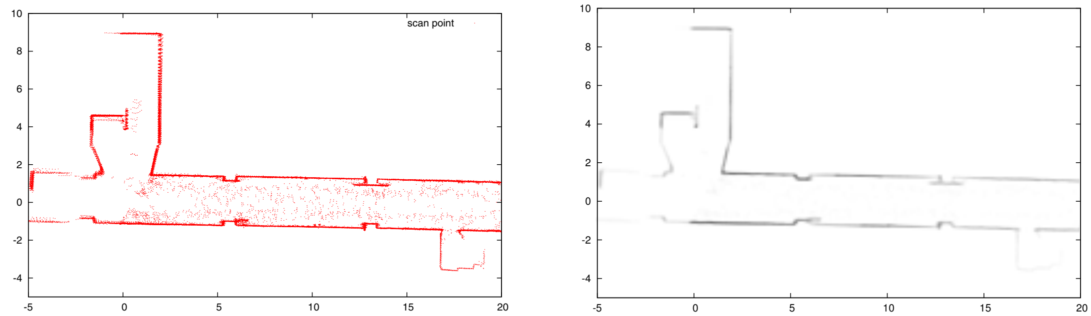
We defined the score of robot position $\mathbf{p}$ as

$$S(\mathbf{p}, Z, M) = \alpha \sum_{i=m} p(\mathbf{z}'_i|M) \quad (2)$$

$p(\mathbf{z}'_i|M)$ is the observed probability of scan point of the position $\mathbf{z}'_i$, and it obtained from the reference scan M. Here, α is given a positive value. The following of this section presents the calculation of the probability $p(\mathbf{z}'_i|M)$.

One of the simple method to obtain the observed probability is to divide the 2D space around the environment into grid pattern cells and count the number of scan points in each cells. In this simple method, however, the small cell is needed to accurately estimate the robot position, and many sample scans are needed to obtain the reliable data. While, the larger cell allows to be easy to collect sample scan points. For this reason, our method is with reference to NDT [7]. NDT is a scan matching method. NDT divide 2D space into grid pattern large cells of about 1m, and the distribution of scan points in each cells is used as reference of scan matching. In NDT, the normal distribution of scan point in each cell represent the shape feature of reference scan and the normal distribution is assumed the local observed probability of scan point in the cell. In our method, the observed probability is calculated using the nomal distribution as the local probability of scan point in the cell. For each cells, the following is calculated to obtain the observed probability. Here, a reference scan point position describes $\mathbf{m} = (x_m, y_m)^T$

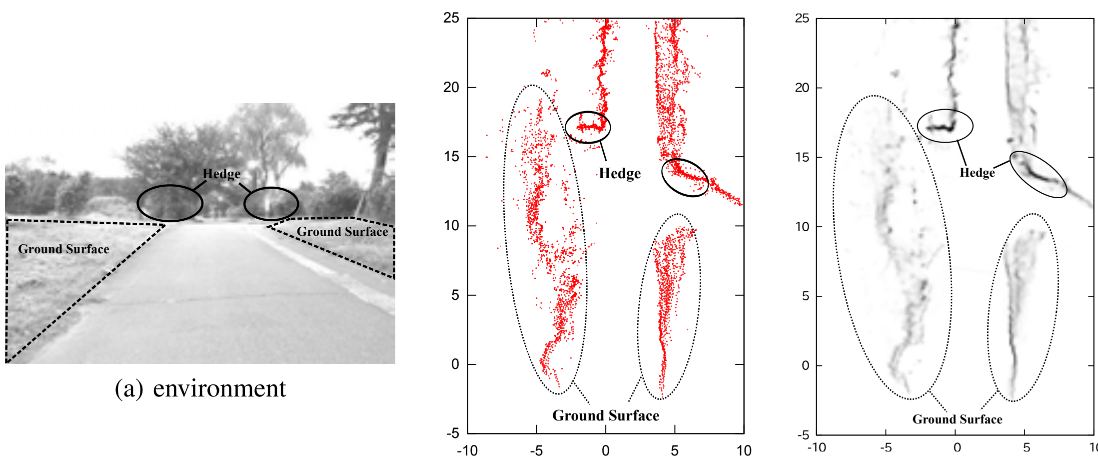
- n_a : the number of scan point in cell a
- $\mu_a = \frac{1}{n_a} \sum_{\mathbf{m}_i \in a} \mathbf{m}_i$: the mean of scan point position in cell a



(a) raw scan data

(b) observed probability

Fig. 5. Observed probability in a corridor environment where walkers exist: (a) shows the raw scans data. The points describes scan points. (b) shows the observed probability of scan points. The black area denotes the high observed probability area.



(a) environment

(b) raw scan data

(c) observed probability

Fig. 6. Observed probability in the environment where the ground surface is observed: (a) shows the picture in the environment. In this environment, the scan of ground surface is unstable and some hedges are observed as landmarks. (b) shows the raw scans data. The point describes scan point. (c) shows the observed probability of scan points. The black area denotes the high observed probability area.

- $\Sigma_a = \frac{1}{n_a}\sum_{\mathbf{m}_i \in a}(\mu_a - \mathbf{m}_i)(\mu_a - \mathbf{m}_i)^T$: the covariance matrix in cell a

The cell that contains a current scan point $\mathbf{z}'_i$ describes a_i and the event that observed a scan point in the cell a_i describes $O(a_i)$. When scan point is observed at $\mathbf{z}'_i$, $O(a_i)$ holds, and $p(\mathbf{z}'_i|M)$ is indicated the following.

$$\begin{aligned} p(\mathbf{z}'_i|M) &= p(\mathbf{z}'_i, O(a_i)|M) \\ &= \frac{p(\mathbf{z}'_i, O(a_i)|M)}{p(O(a_i)|M)} \cdot p(O(a_i)|M) \\ &= p(\mathbf{z}'_i|O(a_i), M) \cdot p(O(a_i)|M) \end{aligned} \quad (3)$$

$p(O(a_i)|M)$ is the probability to observe a scan point in cell a_i. It obtains from the observed

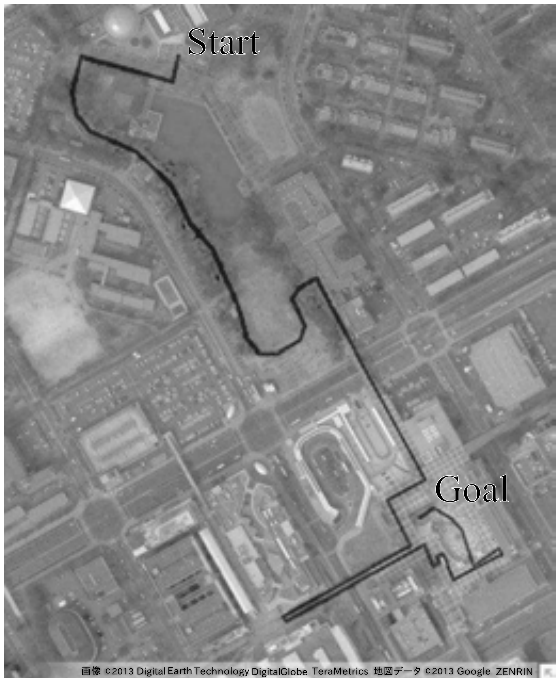


Fig. 7. The route in the experiment

frequency of scan point and solves the following.

$$p(O(a_i)|M) = \frac{n_{a_i}}{N} \tag{4}$$

Here, N is the number of scan point in all of the reference scans.

$p(\mathbf{z}'_i|O(a_i), M)$ is the local observed probability in the cell a_i. It is assumed to follow a normal distribution.

$$p(\mathbf{z}'_i|O(a_i), M) \sim \frac{1}{2\pi\sqrt{|\Sigma_{a_i}|}} \cdot \exp\left(-\frac{(\mathbf{z}'_i - \mu_{a_i})^T \Sigma_{a_i}^{-1} (\mathbf{z}'_i - \mu_{a_i})}{2}\right) \tag{5}$$

Thus, the observed probability $p(z'_i|M)$ is obtained by the following.

$$p(\mathbf{z}'_i|M) \sim \frac{n_{a_i}}{N} \cdot \frac{1}{2\pi\sqrt{|\Sigma_{a_i}|}} \cdot \exp\left(-\frac{(\mathbf{z}'_i - \mu_{a_i})^T \Sigma_{a_i}^{-1} (\mathbf{z}'_i - \mu_{a_i})}{2}\right) \tag{6}$$

Fig.5 and Fig.6 show the examples of the observed probability of scan point by our method. To visualize the observed probability, these bitmap is made by calculating the observed probability in each pixel's position by Equation.6. Fig.5 shows the corrider environment where walking persons exist. Fig.5-(a) shows the raw scan data. There are many scan point indicating the walking persons and walls. Fig.5-(b) shows the observed probability obtained from the scans shown in (a). The feature of walls is extracted because the wall is frequently observed from almost same position. Fig.6-(a) shows the picture of the environment, and (b) shows the scans in this environment. In this environment, the scans of the ground surface around this sidewalk are unstable due to the robot vibration caused by uneaven road surface, while there are some hedges as the landmark. Fig.6-(c) shows the observed probability that obtained from scans of (b). It is confirmed that the observed porbability around hedges is greater than the area where ground surface is observed.

Fig. 8. The robot used in the experiment

IV. Experimental Usage in Real Environment

In this section, the results of experimental usage of our method in a real environment Tsukuba Challenge 2011 [8] is presented to evaluate the method. Tsukuba Challenge is a autonomous robot navigation challenge in the City of Tsukuba, Japan. In Tsukuba Challenge 2011, the robot moved automatically on the 1.2km pedestrian environment shown in Fig.7.

Fig.8 shows our robot. This robot is horizontally equiped with laser scanner Hokuyo UTM-30LX for localization. For localization, we used the particle filter [9]. The number of particles were 500, and each particles move according to odometry model. The particles are evaluated by our method (Equation.2) every 0.1 second for resampling. The reference scans is obtained when the robot moved manually on the route in a priori.

The robot moved on the instructed path. The path has several waypoint and the robot moves on the line between current waypoint and next one. When the robot detected obstacles using laser scanner, the robot plans an avoidance route using A* algrithm. This path made manually with reference to the trajectory when the robot moved manually in the route in a priori.

In Tsukuba Challenge 2011, there was a total 9 days trial and final runs, and the robot completely ran the route 5 times. Fig.9 shows snapshots during trials when the robot completely runs the route and the observed probability around each spot. The arrows in each figure shows the camera position. Fig.9-(a) and (b) shows the environment where are people. In the environment where the robot was prevented landmark observation by many moving object, the robot was able to estinamte self position. In these case, the area around wall had high observed probability and these feature is weighted greater than moving object. In Fig.9-(c), the robot observed ground surface on the front, and it's measurement is unstable. The observed probability indicates that the measurement of the ground surface is widely distributed. Hence, the ground surface feature is not used as a effective feature for localization. In Fig.9-(d), the robot ran on the narrow slope path and the complex objects in the left of robot is unstably measured. It indicate this locaization method allows to accurately estimante the robot position. From this experiment, this method is an effective for unstable measurement environment.

V. Conclusion

This paper presented the observed probability of laser scan points for mobile robot localization. In real environment such as urban sidewalks, the laser scanner measurement is unstable due to varius noise such as moving objects, change of scanning area by tilt or vibration of robot, and so on. And the unstable measurement makes difficult to estimate robot position. This method use the observed probability of scan points for mobile robot localization. The observed probability allows to extract the feature of static object. The observed probability is statistically obtained from multiple scans as reference scan. In the experiment, the robot ran in the pedestrian environment in Tsukuba Challenge 2013 to verify the effectiveness of this method, and this robot moved completely the route of about 1.2km. The future work is to compare with other method to verify the robustness for various case of unstable measurement.

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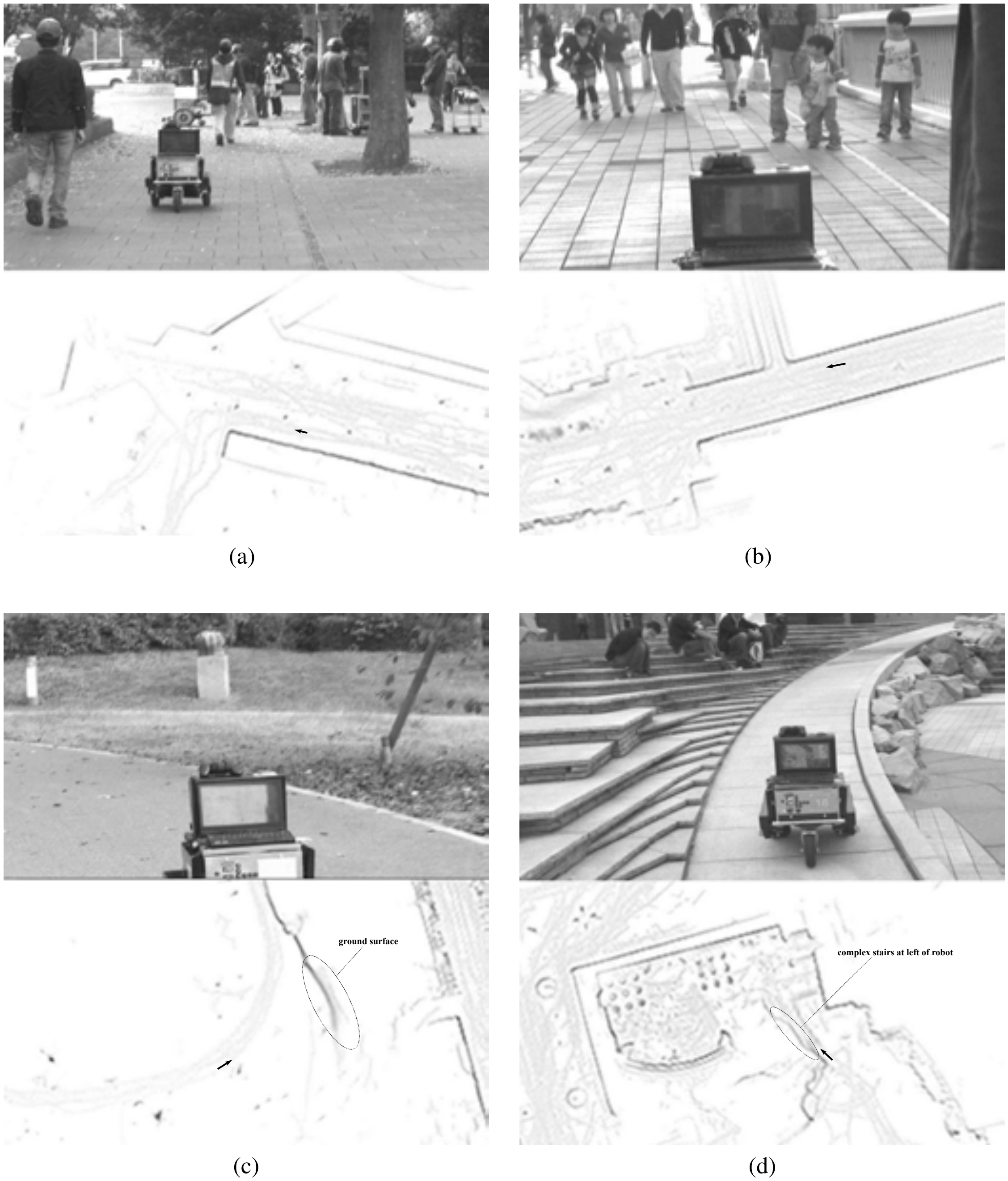

Fig. 9. Snapshots during trials and observed probability: This figure shows sevral snapthot in trial and the observed probability in each place. Each arrows shows the camera position when took the snapshot.