3ZG-04

Cross Iterative Method for Angle Estimation and Ground Plane Detection with RGB-D Camera

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1. Introduction

As a fundamental problem of scene recognition, ground plane detection has been widely used in numerous applications ranging from moving object tracking to automatic identification and intelligence robotics. Variety of backgrounds and scenes make it even more challenging in the computer vision area. Most existing approaches used the Euclidean distance as the key to estimate the ground plane from a set of observed data, where RANSAC has been frequently applied due to its practicality and convenience [1, 2]. Recently, many approaches tend to use probability instead of Euclidean distance to detect ground plane [3]. Although these approaches have achieved good performance, the pose of the camera was not been discussed. Since the camera pose is an important factor for describing the ground plane in the scene, the pose determination helps to improving the accuracy and reliability of the ground plane detection.

2. AGP-CIC

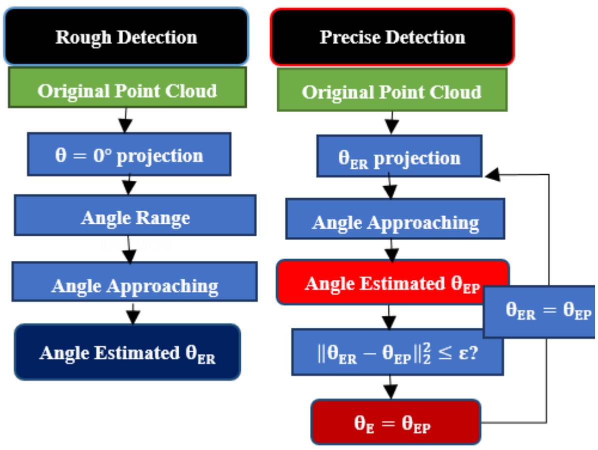

Figure 1. Flow chart of our algorithm

In this paper, we propose a novel ground plane detection algorithm named AGP-CIC (*Angle-Ground Plane Cross Iterative Convergence*) which uses the point cloud obtained from a RGB-D camera to detect the ground plane and the camera tilt angle. In contrast to most existing approaches, the camera tilt angle is used as a feedback to the detection to improve its accuracy. The benefit of our algorithm is that once the initial camera tilt angle is set, it is refined iteratively without requiring a particular calculating method.

The flow chart of our algorithm is shown in Fig. 1. It consists of two procedures, 1) rough detection (RD), and 2) precise detection (PD). In the RD procedure, an approximate range of a RGB-D camera angle is decided with the probability theory. The PD is a feedback procedure that determine the precise angle by minimize the error calculated with an evaluation function within the range we get in RD.

2.1 θ-projection

We propose a new method named θ-*projection* for updating the selection of point cloud. For a given point cloud and a certain angle θ that is close to the camera tilt angle θ_C, it is considered that after projecting the points onto the normal vector of ground plane, the most concentrated part of the distribution should be around the height of ground plane. In the ideal situation, when the integration of the height distribution probability density reaches a maximum within a certain range, the points in this range can be seen as the ground plane. According to this, a method named θ-*projection* is proposed to detect ground plane. In this method, we employ Kernel Density Estimator (KDE) to calculate the probability density of height distribution. We choose Gaussian Kernel as the kernel here, and the density is expressed as

$$p(y \mid \theta) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\sqrt{2\pi}h}\exp\left(-0.5\frac{y-y_{\theta i}}{h}\right) \qquad (1)$$

where h is the bin width of the height distribution histogram and $y_{\theta i}$ is the height of each point after projected. After we obtain the density, as talked before, a certain range within which the integration reaches a maximum should be decided. We use

$$\Delta = [y_{max} - \tilde{\sigma}, y_{max} + \tilde{\sigma}] \qquad (2)$$

to express the certain range where

$$y_{\max} = \operatorname*{argmax}_{y \in [0,H]} (p(y \mid \theta)) \qquad (3)$$

and H is the maximum height. The points in range Δ given by Eq.2 are regarded as the ones on the ground plane.

We use θ-*projection* in both RD and PD for updating the selection of point cloud. Next we describe these two procedures respectively.

2.2 Rough Detection (RD)

2.2.1 Angle Range Determination

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For the original point cloud $\boldsymbol{C_{org}}$, the initial angle θ_0 is set to be 0. We select points from $\boldsymbol{C_{org}}$ with $\theta - projection$ to obtain a new point cloud $\boldsymbol{C_0}$ and the variance $\boldsymbol{\sigma_0}$. For the same $\boldsymbol{C_{org}}$, with an appropriate angle, the variance obtained after $\theta - projection$ should be small, in other words, the distribution should be sharp. According to this, we use Binary Search Tree to determine an appropriate range of angle, that is, find a maximum angle $\boldsymbol{\theta_R}$, and the right answer should be within [0, $\boldsymbol{\theta_R}$]. When using a larger angle for $\theta - projection$, the variance obtained gets larger than $\boldsymbol{\sigma_0}$. With the $\boldsymbol{\theta_R}$ determined, $\theta - projection$ is implemented on $\boldsymbol{C_0}$, after which $\boldsymbol{C_R}$ is obtained and used for angle approaching.

2.2.2 Angle Approaching

For each $\boldsymbol{\theta_i} \in [\boldsymbol{0^\circ}, \boldsymbol{1^\circ}, \ldots, \boldsymbol{\theta_R}]$, we implement $\theta - projection$ on $\boldsymbol{C_R}$ respectively. After we get the updated point cloud $\boldsymbol{C_{\theta_i}}$, based on the idea that more points would be detected when $\boldsymbol{\theta_i}$ is close to the actual value, we calculate

$$P_{\theta_i} = {N_{\theta_i}}/{N_R} \tag{4}$$

Where $\boldsymbol{N_{\theta_i}}$ is the number of $\boldsymbol{C_{\theta_i}}$, and N_R is the number of C_R. We define the most appropriate angle should be

$$\theta_{ER} = \arg\max_{\theta_i} P_{\theta_i} \tag{5}$$

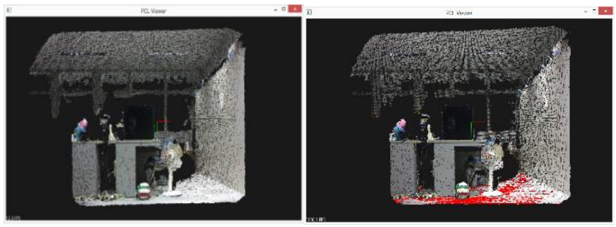
This method for angle approaching will be used in PD as well.

2.3 Precise Detection (PD)

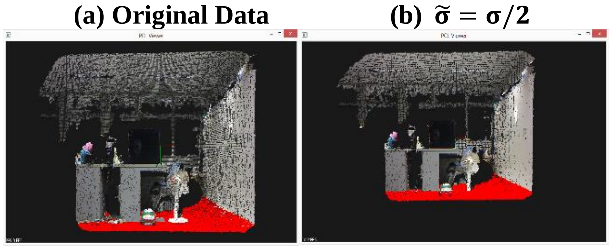
In this procedure, we focus on finding the angle precisely. For the estimated $\boldsymbol{\theta_{ER}}$, we feed it back to the original point cloud (OPC) for updating the selection, after which the obtained point cloud is expressed as $\boldsymbol{C_{ER}}$. With a small deviation, we define the range as $\boldsymbol{\theta_{Pi}} \in [\boldsymbol{\theta_{ER}} - \boldsymbol{\theta_\varepsilon}, \boldsymbol{\theta_{ER}} + \boldsymbol{\theta_\varepsilon}]$ which is used for angle approaching. As shown in Fig.1, by using the angle approaching described in RD, the output $\boldsymbol{\theta_{EP}}$ is compared with $\boldsymbol{\theta_{ER}}$ and considered as the result until the constraint condition $\|\boldsymbol{\theta_{ER}} - \boldsymbol{\theta_{EP}}\| \leq \boldsymbol{\varepsilon}$ is satisfied, otherwise $\boldsymbol{\theta_{EP}}$ will be feedback to the OPC and repeat the iteration. When $\boldsymbol{\theta_{EP}}$ is decided, points detected under this angle will be considered as ground plane.

3. Experiments

We implemented large number of experiments to confirm the effectiveness of the proposed algorithm. The original input data is shown in Fig.2 (a). The parameter mainly affecting the result is $\tilde{\sigma}$ (see equation(3)). Fig.2(b)-(d) shows results under different $\tilde{\sigma}$, where the best consequent came out when $\tilde{\sigma} = \sigma$. Over-detection and lack-detection were obtained when $\tilde{\sigma}$ was either too large or too small. Meanwhile, lots of experiments has proved that in this range ($\Delta = [y_{max} - \sigma, y_{max} + \sigma]$) the desirable outcome can be obtained, which is considered to be reasonable according to that the integration in this range can reach 68% of the entire value of normal distribution.



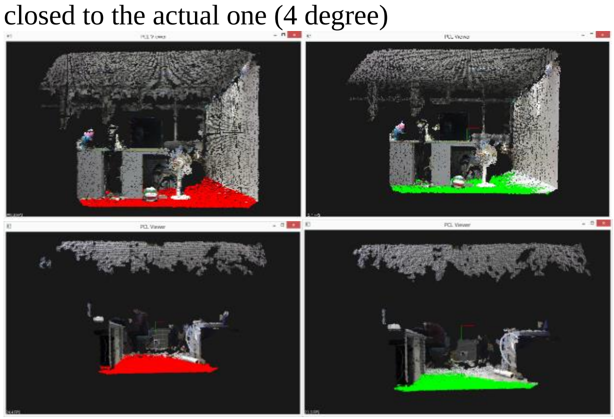
(a) Original Data **(b) $\tilde{\sigma} = \sigma/2$**



(c) $\tilde{\sigma} = \sigma$ **(d) $\tilde{\sigma} = 1.5\sigma$**

Figure 2. Experiment results with different $\tilde{\sigma}$

We compare our algorithm with RANSAC as well. In Fig.3(b), with RANSAC, the ground plane was not detected completely as Fig.3(a). Meanwhile, the camera angle we leaned was 3.8 degree, which is closed to the actual one (4 degree)



(a) Our algorithm **(b) RANSAC**

Figure 3. Comparison with RANSAC.

4. Conclusion

In this paper, we have proposed an innovative approach used for ground plane detection and camera angle estimation. Large number of experiments have been implemented and proved the accuracy and effectiveness of our approach. We plan to innovate it for multi-ground plane detection and apply it in more researches such as moving object tracking.

Reference

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