A Realtime Algorithm for Distinguish Obstacle from Accessible Area in 3D Scene

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Abstract. A learning algorithm based on Hidden Markov random field model is designed, and three-dimensional data is extracted, and the robot is used as an experimental platform. In the process of recognition, obstacle areas and feasible areas are distinguished by template matching, and the accessible areas and obstacle areas of the scene around the robot are obtained by classification results. According to the state of the robot itself, the position and direction vectors of the robot are calculated. The robot adjusts its attitude under the control of the output vector, so as to avoid obstacles and move to the target point. Finally, it is proved that the experiment has ideal real-time performance, so it has an extensive practical application foundation.

1. Introduction

The disparity map obtained by binocular view matching represents depth information [1]. The 3D point information represented by the scene can be obtained by the projection of the depth map [2]. A new algorithm for identifying obstacle regions and passable regions in three-dimensional space by Hidden Markov random field model is proposed. The learning algorithm based on HMM (Hidden Markov Model) random field model is used to divide the three-dimensional information of the scene. Through the study of barriers to regional models, using the Viterbi algorithm for optimal state sequence, after the identification process will be divided into three-dimensional scene space barrier region and accessible areas. Provides an environmental basis for the robot's motion planning within the scene space.

2. Distinguish Obstacles from Accessible Areas

The three-dimensional information of the scene is obtained through the disparity map, but the robot cannot perform path planning in the three-dimensional space. By constructing 3D point information and dividing the space around the robot into obstacle areas and feasible areas based on the 2D ground, the work of machine path planning is possible. [3] According to different application requirements, the criteria for distinguishing obstacle area and feasible area are not completely consistent. After obtaining three-dimensional scene point information, obstacle area and passage area should be divided based on scene information to control robot passage conditions, to determine the workspace required for robot path planning [4].

There are many ways to divide the ground into regions, but the real-time performance of the divided regions is easy to be misclassified. The HMM is used to divide a 3D scene into regions, and divides the ground region according to the roughness of the ground. Passable area and impassable area. HMM is a method for pattern classification of a continuous sequence [5], which can divide the observed ground into different regions on the basis of learning and has good universality and
adaptability.

The implicit Markov model is expressed by a 5-tuple \((S, V, A, B, \pi)\), where \(S\) is the possible state of the model, and \(S = \{1, 2, \ldots, N\}\), \(V\) are all possible discrete values of the observation, \(V = \{v_1, v_2, \ldots, v_M\}\), \(A\) is a state transition matrix of \(N\) rows and \(N\) columns, \(A = \{a_{ij}\}\), \(a_{ij} = P(q_{t+1} = j \mid q_t = i), 1 \leq i, j \leq N\). \(\pi\) represents the initial state probability distribution \(\pi = \{\pi_i\} = P(q_1 = i)\), which is the probability of selecting a certain state at the initial time.

HMM is a very powerful probabilistic tool [6-7]. In the case of a given model, the probability of an area's topographical observations can be calculated, so that the terrain rugged model of the area can be classified. The ground is divided into passable area and obstacle area. The determination of the obstacle area is mainly described by the ruggedness model of the ground. Document [8] classifies the rough terrain method into 7 types. When the observation area conforms to the 7 types of areas, the observation area is defined as the obstacle area, otherwise the observation area is defined as the passable area. Use HMM to classify the ground to achieve the desired goal.

2.1. The discrete hidden Markov model is used to describe three problems of ground robustness.

(1) Model learning training

The state number is taken as 8 so \(S = \{1, 2, 3, 4, 5, 6, 7, 8\}\), the initial state probability distribution \(\pi = \{1/8, 1/8, 1/8, 1/8, 1/8, 1/8, 1/8, 1/8\}\); Rugged area is represented by 7 templates. By training samples, a set of probability matrix \(B_i\) and probability matrix \(A_i\) of state transition can be obtained, which are expressed as discrete implicit Hidden Markov Model \(\lambda_i = (A_i, B_i, \pi_i)\) \((i = 1 \sim 8)\).

(2) Optimal estimation of state sequence

After \(\lambda_i = (A_i, B_i, \pi_i)\) is obtained from step (1), the unclassified observed altitude region \(O = \{o_1, \ldots, o_T\}\) is calculated, and the optimal state sequence \(Q = q_1, q_2, \ldots, q_T\) is calculated, and \(P(O \mid \lambda_i)\) is generated with the maximum probability.

(3) Estimating the problem and classifying the ruggedness

Obtained in step (1) using \(\lambda_i = (A_i, B_i, \pi_i)\) and \(Q = q_1, q_2, \ldots, q_T\) obtained in step (2) is calculated \(P(O \mid \lambda_i)\), formula is as follows:

\[
P(O \mid \lambda_i) = \pi_{q_1} \left( \prod_{t=1}^{T-1} b_{q_t}(o_t) a_{q_t q_{t+1}} \right) b_{q_T}
\]

Maximum probability model by the formula \(\lambda_i^*\)

\[
i^* = \arg\max_i P(O \mid \lambda_i)
\]

Where \(i^*\) is the classification result of observation \(O\). When \(i^*\) is \(1 \sim 7\), the area is an impassable area. When \(i^*\) is 8, the area is a passable area. The Baum Welch algorithm is used in the model learning process, and the Viterbi algorithm is used in the state sequence solving process. The estimation problem is solved by using the forward algorithm to complete the scene region [9].

The optimal state sequence is calculated by taking the observation sequence of 30x30 size from the three scenes [10], and the scene region is divided. When the observation result conforms to any of the seven conditions, it is judged as the obstacle region. The cumulative number of obstacle areas exceeds the minimum limit (take 4 in the experiment), and the area is determined as the obstacle area. Figure (a) is the actual acquisition of the 3D scene obtained by the disparity map, Figure (b) is the effect map of
the obstacle area identified by the 3D scene.

Figure 1. Recognition results in obstacle area of the 3D scene map

In the scene obstacle area recognition, in order to reduce the redundant calculation of the environment recognition algorithm, the height threshold is set according to the robot's ability to cross obstacles, and the height threshold is set to \((-H_{low}, +H_{high})\). When the height of the scene three-dimensional point exceeds the threshold, the obstacle area is directly divided into No identification is required, as shown in the rectangular obstacle area in Figure (b). For the above figure, the entire recognition process consumes less than 10ms, and the algorithm recognition speed is ideal.

3. Experiments

The mobile robot and sensors.

Figure 2. Robot parameters used in experiments of the artificial map

Experiments were carried out using artificial moment algorithm, wall walking algorithm and the algorithm. The experimental results obtained in the first type of artificial map are shown in Figure 2.
| Manual Map 1 | Artificial Torque Algorithms | wall-following algorithm (Clockwise) | wall-following algorithm (anticlockwise) | proposed algorithm |
|-------------|-----------------------------|-------------------------------------|----------------------------------------|-------------------|
| operation steps (steps) | 302 | 330 | 388 | 231 |
| path length (pixels) | 1148 | 1300 | 1678 | 989 |
| Planning time (ms) | 10ms | 10ms | 10ms | 10ms |

Figure 3 shows the process of using the algorithm of this paper to move to the target point.

Figure 3. Robot walking perspective screenshot

4. Results
A new algorithm for recognizing obstacle zones and accessible zones in three-dimensional space using hidden Markov random field model is proposed. In the process of recognition, the obstacle area and feasible area are successfully distinguished by template matching, and the accessible area and obstacle area of the scene around the robot are obtained by classification results. The task of the robot was successfully accomplished in the experiment, and the real-time performance and reliability of the algorithm were proved.
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