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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSI*net*

Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Path Planning in Unknown Environment for Mobile Robots Based on Improved Bayes and PSO

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Abstract: This study presents an environment perception method using for mobile Robots based on ultrasonic probability grid map feature points extraction and matching. Low-cost ultrasonic sensors as the design scheme of distance measuring is adopted. Aiming to obtain the probability of grid map update effectively, an improved Bayesian formula is proposed. To realize synchronous positioning and map construction, dynamic random objects are related to the map with edge detection algorithm. Then the motion of the next step of robot is planned by improved particle swarm algorithm. The result of the numerical simulation shows that the novel particle swarm optimization is effective and can find the more optimal global solutions with high efficiency compared to the basic PSO. The simulation result shows that the method proposed in this study is feasible and effective and the result obtained is effectively to the application of robot in complex environment and realize real-time dynamic collision avoidance path planning.

Key words: Mobile robot, synchronous positioning, map construction, data fusion technology, path planning.

INTRODUCTION

Path planning focused on finding an optimal path for robot to move from the start position to the target point according with certain performance conditions (Tian and Gao, 2007). The basic problems included environment description, search strategy and so on. The obstacles are assumed to be stationary in unknown region can be detected with sensors. it is to be noted that path planning plays an important role for mobile robots in unknown environment. So, far as the real-life industrial case-study is concerned to achieve the path planning for the mobile robot in unknown environment, robot should define its current location that is, to obtain the robot's position and orientation which relative to a fixed coordinate. the position and orientation is calculated by vibration of photoelectric encode, according to the measured incremental motion's values of electric motors, requiring no certain environment information. But in this case, measurement noise accumulates continuously. And the measurement noise may annihilate the actual values in a long path. To overcome the shortcoming, robot can locate its position perceiving environment information with many sensors. However, there is redundant information. To obtain more accurate measurement results, the multi-sensor data fusion algorithms are employed to reconstruct the outputs of each sensor, especially the characteristic information of blocks (Thrun, 1998). The combining algorithm is proposed in this study for global optimum path planning of mobile robots. The obstacles are

assumed to be stationary in unknown region which can be detected with sensors. A novel location algorithm of Min-Max+LI employs firstly to presetting for environment obstacle, by which environment information is produced. Based on the information, an improved Bayesian statistics which fusing environment information, is used to map the robot's surrounding environment. After that, the path can be planned by the modified Particle Swarm Optimization (PSO) algorithm and the feasible route for mobile robot in dynamic environment in unknown region is achieved.

MODELING OF THE ROBOT ENVIRONMENT

Mobile Robot's navigation and terrain avoidance need environmental information supporting. That's why Mobile Robot perceive external environment with sensors (i.e., ultrasonic transducer and infrared sensor) and map it by information processing mechanism (Sungbok and Hyunbin, 2010). As shown Fig. 1.

Robot needs to move from the start position S to the target point G in unknown environment information region Ω . There are some blocks in the region. First, Ω is cut apart into raster and the coordinates of the raster is given by:

$$\Omega = \{(x_i, y_i) \in \mathbb{R}^2 | i \in \Gamma\} \quad (1)$$

where, Γ defines as the finite set of the raster coordinates. If raster is occupied, it means that there are blocks. Robot receives environment information and self-position

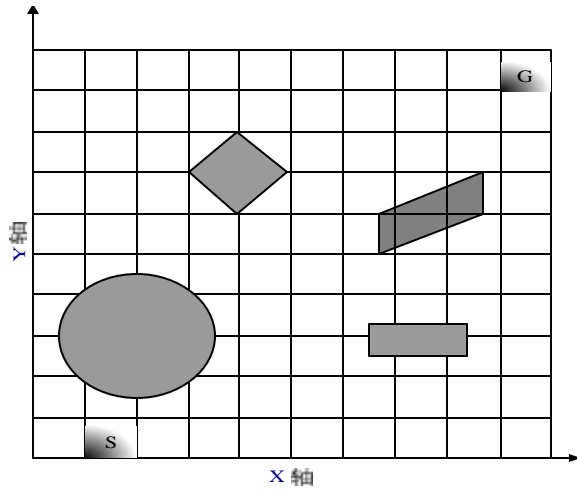


Fig. 1: Unknown region Ω

information with sensors, builds occupying space map using Bayes and programs an optimal or near-optimal path with no blocks by PSO.

MERGING SCHEMES

Research of data fusion method: The robot makes its plan before the beginning of each interval. A mobile robot collects information of its neighborhood using the sensors during actual navigation. Therefore, based on the prior knowledge of navigation control, more accurate and reliable information of environment is achieved by integration of data computed by the Multi-sensor Data fusion. This study adopts classical Bayesian method data fusion (Sun *et al.*, 2006). If the coordinates observed by multi-sensors are compatible, Bayesian inference is used to fuse the collected data directly. Or, the data should be processed indirectly. And before fusing the measured data, the consistency should be tested. Conventional testing methods: distance, experience to determine methods, neural networks, etc. probability distance, one of the distance methods, is adopted in this study to test the consistency, as Eq. 2 shows:

$$\begin{cases} d_{ij} = \left| \int_{z_i}^{z_j} p_i(z|z_i)p_i(z_i)dx \right| \\ d_{ji} = \left| \int_{z_i}^{z_j} p_j(z|z_j)p_j(z_j)dx \right| \end{cases} \quad (2)$$

where, p_i, p_j are prior probability for the two sensors, d_{ij}, d_{ji} is the distance probability.

$p(z|z_i), p(z|z_j)$ is condition probability. Γ threshold, if $d_{ij}, d_{ji} \leq \Gamma_g d_{ij}, d_{ji} \leq \Gamma_g d_{ji}$, then Two sensor data fusion, else identified as inconsistent and then re-measurement.

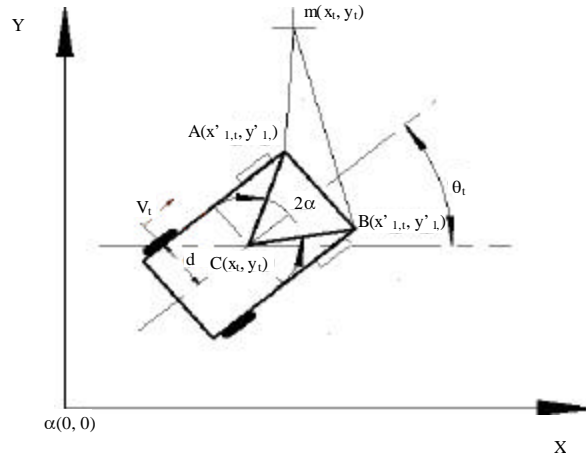


Fig. 2: Modeling of the information observation

Modeling of the environmental information: Supposed the robot's pose information is s_k at time t . To simplify the calculating, robot pose information as a collection of particles, in which the particles' pose information is $s_k = (x_k, y_k, z_k)$. PSO updating equation $p(s_k|s_{k-1}, u_k)$ as follows:

$$s_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} \\ y_{k-1} \\ \theta_{k-1} \end{bmatrix} + \begin{bmatrix} v_{k-1}\Delta t \cos \theta_{k-1} \\ v_{k-1}\Delta t \sin \theta_{k-1} \\ \frac{v_r(k-1) - v_l(k-1)}{2d} \Delta t \end{bmatrix} + \begin{bmatrix} \xi_1(k) \\ \xi_2(k) \\ \xi_3(k) \end{bmatrix} \quad (3)$$

Where:

$$v_{k-1} = \frac{v_r(k-1) + v_l(k-1)}{2}$$

v_r, v_l are the speed of Robot's right and left wheel, respectively. $2d$ is the distance from the right wheel to left wheel.

Observational model of Robot particle is as shown in Fig. 2, where: $A(x'_{1,t}, y'_{1,t}), B(x'_{2,t}, y'_{2,t})$ are the sensor coordinates, $z_t(\hat{p}_{1t}, \hat{p}_{2t})$ is the distance from point A to point B at time t , $C(x_t, y_t)$ is the center of robot, in that way, it is the coordinates of particle s_t , $|AB| = 2d, |CA| = |CB| = 1, p(z_k|s_k)$, coordinate translation formula which characteristics of the environment corresponding observational models at time t , is deduced according to reference (Zhao *et al.*, 2010) that is as follows:

$$\begin{cases} \hat{x}_t = x_t + 1 \cos(\theta_t + \alpha) + 2L_1 \sin 2\alpha \sin 2\theta_t - 2H_1 \sin 2\alpha \cos 2\theta_t \\ \hat{y}_t = y_t + 1 \sin(\theta_t + \alpha) - 2L_1 \sin 2\alpha \cos 2\theta_t - 2H_1 \sin 2\alpha \sin 2\theta_t \end{cases} \quad (4)$$

At time t , the coordinate of environmental characteristic points are $m_t = [\hat{x}_t, \hat{y}_t]$.

Constructed grid map and map matching: There are defects of large scattering angle and poor direction of ultrasonic sensors which induce uncertainty of distance measuring information. Need to use specific algorithm, such as the average distribution model and the middle arc model, to process the distance information. This study adopts one-dimensional Gaussian model of the sensor:

$$p(z_t | z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(z_t - z)^2}{2\sigma^2}\right) \quad (5)$$

According to the measured information of each grid is divided into the possession of the possession, empty, unknown for information to be obtained is ρ , then corresponding probability in the occupied is 1. Front of the grid in the grid the probability of all the occupied are 0, State of the other grid all unknown, the occupied are 0.5, Ranging information on the use of the modified Bayesian method to estimate the log-likelihood ratio method (log-odds method) for data fusion, Where m_t is the posterior probability, the $z_t = (z_0, \dots, z_t)$ means observational information, the $s_t = (s_0, \dots, s_t)$ is the robot trajectory at time t , initialization of $p(m_t)$ is 0.5, then:

$$\begin{cases} O(m_t | z_t, s_t) = \frac{O(m_t | z_t)}{O(m_t)} \times \frac{O(m_t | s_t)}{O(m_t)} \times O(m_t) \\ I_{xy}^t = \log \left[\frac{p(m_t | z^t, s^t)}{1 - p(m_t | z^t, s^t)} \right] = \log \left[\frac{p(m_t | z_t, s_t)}{1 - p(m_t | z_t, s_t)} \right] + I_{x,y}^t \end{cases} \quad (6)$$

Robot in the perceived value of new observations $z_t = (\hat{\rho}_{1t}, \hat{\rho}_{2t})$ and environmental characteristics of its matching set of points m^t . Matching formula is as follow:

$$f(s_t, m) = \min_{m_i \in m} \{d_{(m_i, s_t)}\} \quad (7)$$

where, $d(m_i, s_k)$ is the distance from posture coordinates to point of environmental characteristics coordinates m_i , $f(s_t, m)$ is the shortest distance between particles and the feature points of environmental characteristics coordinates m^t in time t . Set the threshold T_h is the maximum matching error, if $f(s_t, m) < T_h$, then returns true value, means match succeeds, otherwise, the match fails.

BASED ON IMPROVED PARTICLE SWARM ROBOT PATH PLANNING

Improved PSO algorithm: In this study, PSO optimization method based on robot path planning (Bailey and Durrant-Whyte, 2006). Supposed the dimension of the searching space is D , the number of particle is N . the

position of the particle is represented as $x_i = (x_{i1}, \dots, x_{iD})$. The $p_i = (p_{i1}, \dots, p_{iD})$ is the best position searched by now and the whole particle swarm's best position is represented as $p_g = (p_{g1}, \dots, p_{gD})$. The velocity of each particle is represented as $v_i = (v_{i1}, \dots, v_{iD})$. In each iteration, the p vector of the particle with best fitness in the local neighborhood, designated g and the p vector of the current particle are combined to adjust the velocity along each dimension and a new position of the particle is determined using that velocity. The two basic equations which govern the working of PSO are that of velocity vector and position vector given by:

$$v_{id}^{k+1} = \omega v_{id}^k + c_1 r_1 (p_{id}^k - x_{id}^k) + c_2 r_2 (p_{gd}^k - x_{id}^k) \quad (8)$$

$$x_{id}^{k+1} = x_{id}^k + \alpha v_{id}^k \quad (9)$$

$$\omega = \omega_{max} - \frac{(\omega_{max} - \omega_{min}) \cdot Iter}{Iter_{max}} \quad (10)$$

$$p_g^k = \sum_{i=1}^N p_{id}^k / N \quad (11)$$

where, $d = 1, 2, \dots, D$, k is the current evolutionary generation; w is the inertial weight, c_1 and c_2 are the acceleration constants and r_1 and r_2 are the random number in the $[0,1]$ interval. α is velocity weights and are the random number in the $[0.01, 0.1]$ interval. The research shows that larger w value is useful to avoid the local minimum and smaller w value is useful to improve the convergence speed. The $Iter_{max}$ is the maximum evolution generation, ω_{max} and ω_{min} are the maximum and minimum inertia weights, respectively. Considering the real robot who has max allowed velocity and position, we give constrain:

$$\begin{cases} v_i = v_{max}, & v_i > v_{max} \\ v_i = -v_{max}, & v_i < -v_{max} \end{cases}, \begin{cases} x_i = x_{max}, & x_i > x_{max} \\ x_i = x_{min}, & x_i < x_{min} \end{cases}$$

Fitness function: The fitness function is an important factor for the convergence and the stability of Particle Swarm Optimization (PSO). The collision avoidance and the shortest distance should be considered in path planning. In this study, the collision avoidance can be considered as a restriction which can be solved by using penalty function. The length of the path is to be optimized and then the fitness function is defined as:

$$\begin{aligned} F &= \omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3 + \omega_4 f_4 \\ &= \omega_1 \sqrt{(x_i - x_G)^2 + (y_i - y_G)^2} + \omega_2 \sqrt{(x_i - x_n)^2 + (y_i - y_n)^2} + \omega_3 d_n \end{aligned} \quad (12)$$

The (x_i, y_i) , (x_G, y_G) , (x_n, y_n) is the current node coordinates of particles, respectively. Target object

coordinates, particles reachable node coordinates, d_n is the paththreaten degrees get it from feature points of matching map.

Detailed realization steps:

- Step 1:** Initialize the swarm, including population size, each particle's position and velocity and maximum number of iterations, the starting point and target
- Step 2:** Calculate the fitness of each particle and the path of the posterior probability distribution of the s_i particle based on the above Eq. 3. Then implement feature extraction points, map matching and reality time data fusion on the basis of the Eq. 5-7
- Step 3:** According to the particle update Eq. 8-9 fitness function (12) calculate each particle's the optimal selection p_{ids}^k , select the position of the minimum adaptive value as the global optimum p_{gd}^k
- Step 4:** After the iteration of the particle position as the new starting point which will be updated after the initial point of the position and velocity to assign the first particles, will transform the position after the assignment to the last particle
- Step 5:** If algorithm achieves maximum iterating times or meet the precision requirements, the algorithm and the output of the search out over the optimal path. Otherwise turn to step 2

SIMULATION AND ANALYSIS OF THE RESULT

Some important parameters used in the proposed method, Size of room is $10 \times 10 \text{ m}^2$, Size of grids is $0.1 \times 0.1 \text{ m}^2$, Safe radius is 2 m, Maximal iteration number is 300, Velocity of sound wave is 340 m sec^{-1} , Velocity of robot is 0.2 m sec^{-1} , Velocity of moving obstacles is 0.12 m sec^{-1} , Direction angle of robot is $[0, 2\pi]$. The safe radius is used to avoid that the robot runs into the obstacles. The direction angle is used to define the direction of obstacles and target region according to the current position of robot, then an optimal moving direction for robot can be obtained.

For convenience, in the following simulation, we use RGB color model to depict the robot (blue), obstacles (red), wall (yellow) and target region (green). There exist three static obstacles whose motion can produce pink regions. There exist three obstacles including two mobiles whose motion can produce pink regions. The grey region means that the free room detected by the robot. The motion of the robot can form a white curve. We expect that the robot can arrive at the target region safely, without knocking into any obstacles or the surrounding wall. If we use the symbol D to describe the linear distance between the initial position of robot and its target point, Fig. 3a-d describe the results of $2/5D, 3/5D, 4/5D$ and fitness value line, respectively in stationary environment, Fig. 4a-d describe the mobiles e the results

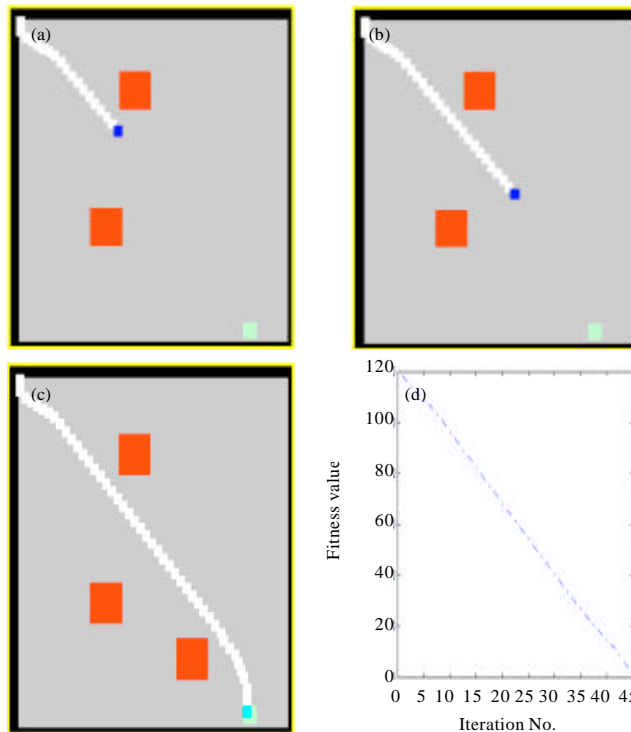


Fig. 3(a-d): Static obstacles of the environmental

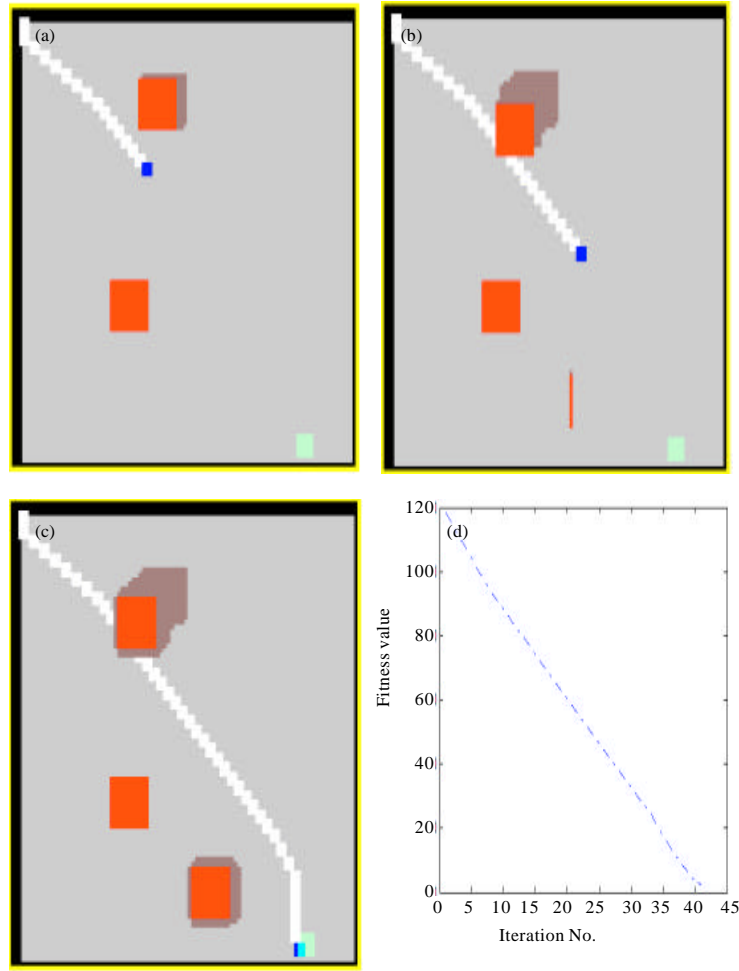


Fig. 4(a-d): Mobiles obstacles of the environmental

of 2/5D, 3/5D, 4/5D and fitness value line, respectively in Dynamic environment. These subfigures sample several representative snapshots for the robot. Figure 3 shows that the robot avoids three static obstacles and finally arrives at the target region. Figure 4 shows that the robot avoids the static obstacle and two mobile ones and finally arrives at the target region.

CONCLUSION

The synchronous positioning and map construction algorithm in static obstacles and dynamic environment are presented based on path planning. After map constructed and synchronous positioned, path planning can be realized according to the perceived state data of random target. Based on the simulation test, the result of the simulation confirms that the method can solve Mobile

Robots achievable to obtain real-time accurate environment information for path planning and to fast avoid obstacles. We have obtained satisfying results and the robustness of trajectories is improved, experimental results show that the algorithm in robot path planning is practical and effective.

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