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Forward Passageway Based Collision-free Target Tracking for Mobile Robot with Local Sensing

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Abstract--This paper proposes a new Forward Passageway (FP) based real-time collision-free target tracking approach for a mobile robot with local sensing. After the position of the target is estimated and localized in robot coordinate system through the combination of vision system and encoder, the sonar information and the target position are converted to a uniform environment model framework called decision-making space. Based on the space, a FP based decision-making is given to endow the robot with the ability to avoid possible obstacles and track the target in unknown environments. Experiment results show the validity of the proposed approach.

I. Introduction

MOBILE robot collision-free target tracking is one of the important research problems on mobile robot, especially in complex and unknown environments. When the target is localized in robot coordinate system, this problem may be regarded as a local path planning from the robot to the target. With the increasing complexity of the environment, local path planning based on sensors receives more and more attentions. The virtual force field approach where the robot complies to a superposed force field is a typical one and the concept of artificial potential field was proposed by Khatib in 1985 [1]**.** Borenstein and Koren developed the Virtual Force Field method [2]. However, this approach suffers from several disadvantages that are inherent to the potential field [3]. In order to solve the problem, researchers present many approaches, such as the vector field histogram method (VFH) [4] and the dynamic window approach [5]. Many advanced intelligent control approaches have also been used to solve the path planning problem, such as genetic algorithm, fuzzy logic and neural networks [6][7]. These approaches may help the robot find a better path.

This paper considers the tracking for a mobile robot moving toward a target with unique colors combination and finally arriving nearby the target. The research is meaningful for multi-robot system. In special cases, the robot might get stuck in local minimum environment. The reason is that the decision is made only by local information and global evaluation can not be obtained. The ability to escape local minimum to some extent is also an essential demand.

Considering the particularity of target and the demand to get rid of local minimum, we adopt vision sensor and encoder to localize the target approximately and the concepts of decision-making space, forward passageway are introduced. On the basis of these, the robot makes the appropriate decisions.

The rest of the paper is organized as follows. Section II gives the description of the proposed approach in detail. Experiments are introduced in Section III and Section IV concludes the paper.

II. Approach Description

A. Problem Description

In this paper, we focus on the real-time collision-free target tracking problem without global localization and the target is represented as a column marker, which is color coded from a finite set of distinctive colors in a pre-defined way [8]. The target marker is divided into the upper part and the lower part, which are labeled as different colors. Different combinations of colors can be recognized as different targets. The task is complete when the distance between the robot and target is less than D_{thres}, which means the robot get the target.

There are four kinds of sensors in the robot system: sonar, infrared sensors, encoder and vision system. Sonar information is used to detect obstacles around the robot. The vision system is used to find the target and estimate the relative position of the target. The information of encoder is used to estimate the relative position of the target when the target is out of the sight of the robot. The infrared sensors information is used to deal with emergent collision avoidance when the robot is very close to an obstacle.

After the robot acquires the sensors information, how to model the environment in a uniform framework is important. Without global coordinate system, it is hard to adopt the traditional grid or geometrical world model. In this paper, only local environment model based on sensors is considered.

It is worth mentioning that it is hard to find the best path because target tracking based on local sensing does not have enough information about the environment. In this case, the global optimization is not considered. On the contrary, we more care about the reliable and efficient collision-free planning in unknown and dynamic environments.

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The Fig. 1 shows the control framework of the robot. The target is estimated and localized in robot coordinate system through the combination of vision system and encoder. The infrared sensors and sonar are used to ensure the safety of the robot. In order to integrate all sensor information in a uniform 2-D framework, a decision-making space is introduced. Based on the space, a FP based approach is proposed to generate the rotation angle θ with the constant velocity v, which will be sent to the actuator of the robot.

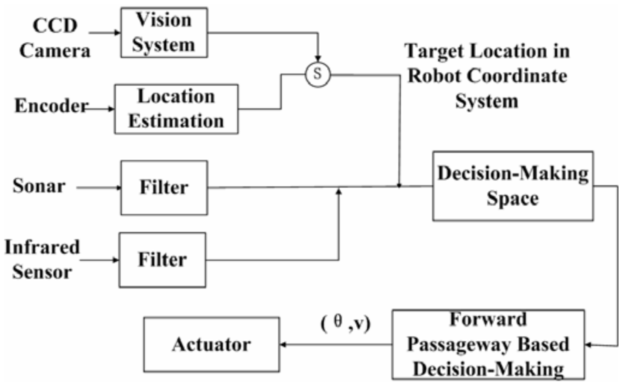

Fig. 1. Overall Control framework of the robot.

B. Target Location Estimation

Without Global localization, a local polar coordinate system Σ is established for the robot. Its pole and polar axis direction are its center and heading of the robot, respectively, which is shown in Fig. 2. The angle 0° is corresponding to the robot heading.

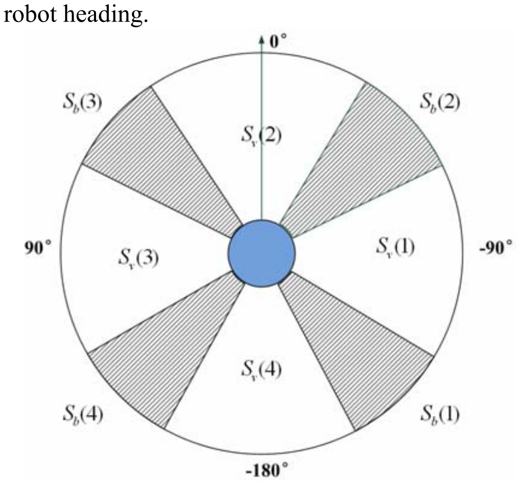

Fig. 2. The model of vision system. The shadow parts are blind sectors.

The experimental robot in this paper has four CCD cameras $S_v(i)(i=1,2,3,4)$ and each has a view sector with an angle zone of $S_v(i)=[-2\pi/3+(i-1)\cdot\pi/2,-\pi/3+(i-1)\cdot\pi/2](i=1,2,3)$, $S_v(4)=[-\pi,-5\pi/6]\cup[5\pi/6,\pi)$ in Σ. Thus, there exist four blind sectors $S_b(i)(i=1,2,3,4)$ with the angle zones of $S_b(i)=(-5\pi/6+(i-1)\cdot\pi/2,-2\pi/3+(i-1)\cdot\pi/2)(i=1,2,3,4)$ in Σ. We denote with (ρ_n^T,θ_n^T) the estimated target position in Σ. When the target is detected by the vision system, color-based object recognition is adopted. The relationship between the actual height of the target marker and the height in the image may be used to estimate the distance between the robot and the target.

We denote with (u,v) a point in the image coordinate system and (x,y,z) is the corresponding coordinate in the world coordinate system. The relationship is depicted as follows.

$$z\begin{bmatrix}u\\v\\1\end{bmatrix}=M\begin{bmatrix}x\\y\\z\end{bmatrix}=\begin{bmatrix}\alpha_x&0&u_0\\0&\alpha_y&v_0\\0&0&1\end{bmatrix}\begin{bmatrix}x\\y\\z\end{bmatrix}\tag{1}$$

where M is the intrinsic matrix of CCD camera, which can be identified by camera calibration.

We label (u_1,v_1) as a point on the top edge of the target marker and (u_2,v_2) as a point on the bottom edge, where the origin of the image coordinate is the center of the image and the left is positive. (x_1,y_1,z_1) and (x_2,y_2,z_2) are the coordinates of these points in the world coordinate system, respectively. $u_1=u_2$, $z_1=z_2$ and y_2-y_1 is the height of target marker. Then

$$\rho_n^T=z_1+d_c=z_2+d_c=\frac{\alpha_y(y_2-y_1)}{v_2-v_1}+d_c\tag{2}$$

where α_y may be identified by camera calibration and y_2-y_1 may be measured before the experiment. v_2-v_1, the height of target marker in the image, may be computed by the image information. d_c is the distance between the camera and the center of robot.

We label (u_T,v_T) as the centre of the target marker. u_d, θ_v are the width of image and the field of view, respectively. If the target is found by $S_v(i)(i=1,2,3,4)$

$$\theta_n^T=\begin{cases}arc\tan(\frac{2u_T}{u_d}\cdot\tan(\theta_v/2))+(i-2)\cdot\frac{\pi}{2} & (i=1,2,3)\\ arc\tan(\frac{2u_T}{u_d}\cdot\tan(\theta_v/2))+\pi & (i=4\wedge u_T<0)\\ arc\tan(\frac{2u_T}{u_d}\cdot\tan(\theta_v/2))-\pi & (i=4\wedge u_T\geq 0)\end{cases}\tag{3}$$

Because of real-time movement, when the target is in a blind sector or not recognized by the robot, the vision system becomes invalid. In this case, encoder information will be used to estimate the position of the target with the previous target information within T_d seconds. If the robot still can not find the target after T_d seconds, it will move randomly. We denote with $(\rho_{n-1}^T,\theta_{n-1}^T)$ the previous target location generated by vision system or deduced through encoder based estimation. D_l, D_r are the distances traversed in previous decision-making cycle by left wheel and right wheel, respectively. Thus, the robot's deflection angle α_n and the distance traversed d_n are calculated as follows:

$$\alpha_n = \arctan(\frac{D_r - D_l}{d_{rl}}) \ , \ d_n = \frac{D_l + D_r}{2}$$

where d_{rl} is the distance between the left wheel and the right wheel. Then we may estimate the target position (ρ_n^T, θ_n^T).

$$\rho_n^T = \sqrt{{\rho_{n-1}^T}^2 + {d_n}^2 - 2\rho_{n-1}^T d_n \cos(\theta_{n-1}^T - \alpha_n)} \quad (4)$$

$$\theta_n^T = \theta_{n-1}^T - \alpha_n + \mathrm{sgn}(\theta_{n-1}^T - \alpha_n)\arccos(\frac{{\rho_{n-1}^T}^2 + {\rho_n^T}^2 - {d_n}^2}{2\rho_n^T \rho_{n-1}^T}) \quad (5)$$

C. Decision-Making Space

Different sensors are mounted different space positions of the robot. It is necessary to uniform sonar and vision information for decision-making in a discrete manner, which is called decision-making space (see Fig. 3) and it represents the local environment model.

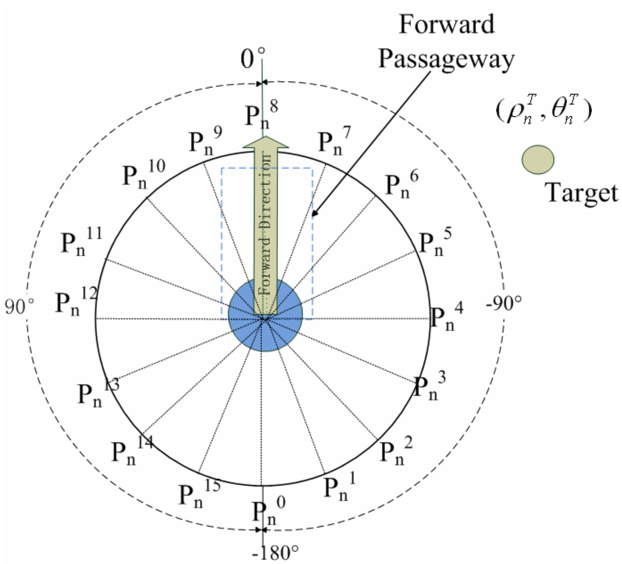

Fig. 3. Decision-Making Space ($K_d = 16$)

Considering the actual application, the robot space is divided into K_d equal parts and K_d is usually a multiple of 4. Thus, the distribution of obstacles obtained through decision-making space can be described as the points set $\varsigma = \{P_n^k(\rho_n^k, \theta_n^k)(k = 0,1,\ldots,K_d - 1)\}$, where $\theta_n^k = \frac{2k\pi}{K_d} - \pi$ and ρ_n^k is the corresponding returned distance. If there exist obstacle in θ_n^k direction, $\rho_n^k < s_{sonar}$, where s_{sonar} is the effective detecting distance of sonar, or else, $\rho_n^k = s_{sonar}$.

D. Forward Passageway Based Decision-Making

Based on the decision-making space, we should plan the path between the robot and the target. Consider the real size of the robot, the Forward Passageway(FP) is introduced. FP is a virtual directed rectangle (see Fig. 3) with the width of Dr_w and the length of Dr_l . It has the following features:

The center of the robot is located in the rectangle of FP.

The direction θ_{FP} of FP is parallel to the robot heading.

The decision is made by rotating a virtual robot R_v in current decision-making space while the environment information remains unchangeable. To avoid the oscillation near obstacles, we label the target direction angle between the robot heading and the ray from the robot to the target as θ_n^g, which indicates the turn state in time n . $\theta_0^g = -\theta_0^T + 2k_g\pi(k_g = 0)$, k_g is adjusted in the algorithm shown in Fig. 4.

We label $\xi = \left\{FP_v^t \middle| \theta_{FP}^t = -\pi + \frac{2\pi}{K_f}t(t = 0,1,\ldots,K_f - 1)\right\}$ as entire search space for R_v, where $K_f = \frac{K_d}{C_{df}}(C_{df} \in N)$ is a multiple of 4. For the virtual robot R_v, we define Ω_t, a subset of ς, to determine whether the passageway FP_v^t is safe.

$$\Omega_t = \left\{P_n^s(\rho_n^s, \theta_n^s)(s = (tC_{df} + j) \bmod K_d) \middle| j \in \left[-\frac{K_d}{4}, \frac{K_d}{4}\right]\right\}$$

Firstly, S_t^k is defined to describe the relationship of a point P_n^k and the zone FP_v^t. P_n^k is within FP_v^t When $S_t^k = 1$.

$$S_t^k = \begin{cases} 1 & (L_s < \frac{Dr_w}{2}) \wedge (L_c < Dr_l) \\ 0 & others \end{cases} \quad (6)$$

where

$$L_s = \left|\rho_n^k \sin((k - tC_{df})\frac{2\pi}{K_d})\right|, L_c = \left|\rho_n^k \cos((k - tC_{df})\frac{2\pi}{K_d})\right|$$

When all obstacle points in Ω_t are not within FP_v^t, it means that FP_v^t is safe. F_n^t is used and the robot may move along the direction of FP_v^t when $F_n^t = 0$.

$$F_n^t = \begin{cases} 1 & S_t^k = 1, \exists P_n^k \in \Omega_t \\ 0 & others \end{cases} \quad (7)$$

After giving the method determining whether a FP is safe, the following is to choose the most appreciate FP based on the target information. The selection criterion is to decrease the deviation angle to the target. Assume that the most suitable FP is described as FP_v^p, the rotation angle for the robot can be obtained $\theta = -\pi + \frac{2\pi}{K_f}p$. The algorithm is given in detail in Fig. 4. If there is no appreciate FP, the robot will only rotate without moving. With this decision-making based on FP, the robot may move to a determined point safely.

Obtain the FP_v^T where the target is located in and

$T=[\frac{(\pi+\theta_n^T)}{2\pi}\cdot K_f]$.

If $(-\pi<\theta_{n-1}^T<-\pi/2)\wedge(\pi/2<\theta_n^T<\pi)$ then $k_g=k_g-1$

If $(\pi/2<\theta_{n-1}^T<\pi)\wedge(-\pi<\theta_n^T<-\pi/2)$ then $k_g=k_g+1$

$\theta_n^g=-\theta_n^T+2k_g\pi$

If $\theta_n^g\ge 0$

If $F_n^{K_f/2}=0$

For $i=0,1,...,$ until $(K_f/2-i)\bmod K_f=T$

If $F_n^{(K_f/2-i)\bmod K_f}=1$

$p=(K_f/2-i+1)\bmod K_f$

Break

End

$p=T$

Else

For $i=0,1,...,$ until $(K_f/2+i)\bmod K_f=T$

If $F_n^{(K_f/2+i)\bmod K_f}=0$

$p=(K_f/2+i)\bmod K_f$

Break

End

There is no appropriate FP

End

Else

If $F_n^{K_f/2}=0$

For $i=0,1,...,$ until $(K_f/2+i)\bmod K_f=T$

If $F_n^{(K_f/2+i)\bmod K_f}=1$

$p=(K_f/2+i-1)\bmod K_f$

Break

End

$p=T$

Else

For $i=0,1,...,$ until $(K_f/2-i)\bmod K_f=T$

If $F_n^{(K_f/2-i)\bmod K_f}=0$

$p=(K_f/2-i)\bmod K_f$

Break

End

There is no appropriate FP

End

End

Fig. 4. Forward passageway selection algorithm

III. EXPERIMENTS

In this section, the experiments are given. The experiment robot AIM is developed by the Institute of Automation, Chinese Academy of Science. The robot has 4 CCD sensors, 16 sonar sensors and 16 infrared sensors, which is shown in Fig. 5.

Four representative experiments are given in different scenes and the motion trajectories are depicted based on the robot's encoder. The experience parameters are as follows: $D_{thres}=60cm$, $K_d=160$, $K_f=40$, $Dr_l=100cm$, $Dr_w=60cm$, $T_d=5$, $d_c=10cm$. The first and second experiments are conducted in static environments,

Fig. 5. The experiment robot AIM. Diameter D_r=48cm.

where the target and obstacles are static. The distribution of obstacles and the trajectory of robot are shown in Fig. 6 and Fig. 7, respectively. From Fig. 6, the robot moves around an obstacle Obs3, then pass through the space between Obs1 and Obs2, and finally gets the target. It is seen from Fig. 7 that the robot moves around a deadlock region formed by three obstacles and get the target successfully.

The third Experiment is shown in Fig. 8. At the beginning, no obstacles exist between the robot and the target, so the robot move straight towards the target. When the robot arrives the point P, an obstacle Obs is put in front of it. The robot adjusts its posture immediately and moves around the obstacle to the target. The experiment shows that the proposed approach endows the robot with the ability to adapt to the environmental changes.

The fourth experiment is designed to verify robot's ability to avoid obstacles while tracking a moving object. The task is completed smoothly and the result is shown in Fig. 9. Through the experiments we have carried out, the proposed approach is considered as an effective one.

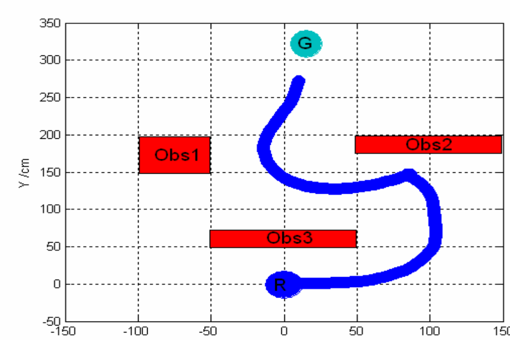

Fig. 6. The result of experiment 1. Obs1: 50cm×50cm, Obs2 and Obs3: 100cm×20cm. R is the robot and G is the target.

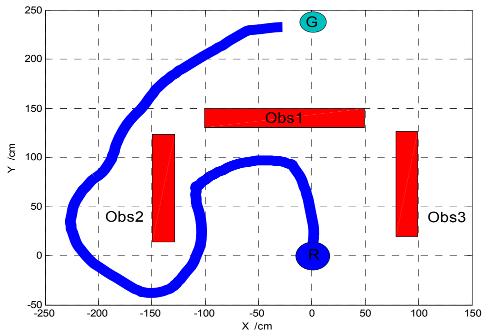

Fig. 7. The result of experiment 2. Obs1: 150cm×20cm. Obs2 and Obs3: 20cm×100cm. R is the robot and G is the target.

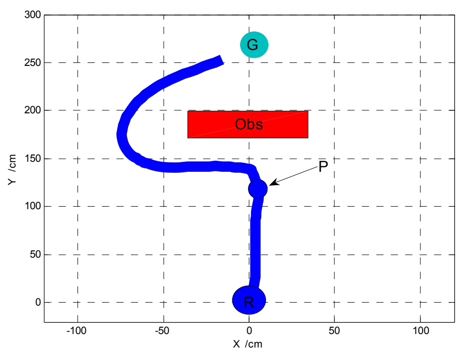

Fig. 8. The result of experiment 3. Obs: 150cm×20cm. R is the robot and G is the target. When the robot arrived P point, an obstacle is put in front of it.

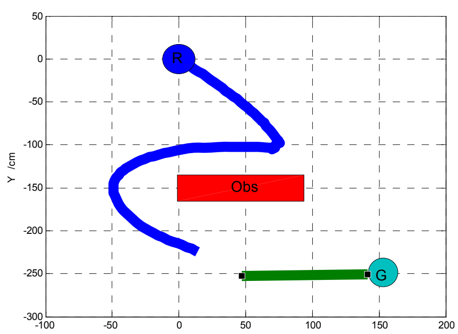

Fig. 9. The result of experiment 4. Obs: 90cm×20cm. R is the robot and G is the moving target. The blue curve is the trajectory of robot and the green one is the target's.

IV. CONLUSION

A forward passageway based collision-free target tracking approach for a mobile robot with vision, sonar and infrared sensors is proposed and its validity is demonstrated through experiments. The proposed local sensing based approach is regardless of global localization and it may endow the robot with the ability to cope with unexpected environmental changes and get the moving target in unknown environments to some extent.

For the proposed approach, the length of forward passageway is a key factor affecting performance. The robot with a long FP may begin to plan process earlier and thus a more long-term decision may be made. However, a greater space will be considered. Therefore, how to choose a suitable FP is an important problem, which will be discussed in future.

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