An Intelligent Control System for Mobile Robot Navigation Tasks in Surveillance

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Abstract. In recent years, the autonomous mobile robot has found diverse applications such as home/health care system, surveillance system in civil and military applications and exhibition robot. For surveillance tasks such as moving target pursuit or following and patrol in a region using mobile robot, this paper presents a fuzzy Q-learning, as an intelligent control for cost-based navigation, for autonomous learning of suitable behaviors without the supervision or external human command. The Q-learning is used to select the appropriate rule of interval type-2 fuzzy rule base. The initial testing of the intelligent control is demonstrated by simulation as well as experiment of a simple wall-following based patrolling task of autonomous mobile robot.

Keywords: mobile robot navigation, moving target, patrol, intelligent control, fuzzy Q-learning.

1 Introduction

The intelligent mobile robots technology has widespread applications at present and in the future. Applications of robotics have been applied to home services, health care and military missions such [3]-[5], etc. Developing various intelligence services, for example intelligent surveillance and patrol systems, is of emerging demand to support human society [6]-[7]. As an intelligent mechatronics system, the mobile robot needs to integrate algorithms related to environment sensing for obstacle detection and SLAM, behavior and route planning, controlling and executing [8]. The focus of its development is on how to make the mobile robots capable of safely, effectively and efficiently operating in various ways in real, unknown environments which may involve interacting with human activities. This requires developing a navigation method that incorporates enough functionalities, in addition to the basic obstacle avoidance and stationary target reaching modes. In this paper, we are interested in using mobile robot for surveillance tasks in various environments. The surveillance by a mobile robot contains target tracking or pursuit, wall following and obstacle avoidance. For intelligent control of mobile robot for navigation, fuzzy control is able to deliver a satisfactory performance in face of unmodelled robot dynamics, uncertainty and imprecision of sensing and actuating devices [9]-[11]. It has been widely applied to the design of robot speed and orientation steering controller because of the following reasons: 1) Control rules are more flexible, thus it can simplify the

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complex system; 2) The controller can emulate the human decision making; 3) It does not need a detailed model of the plant, and it replaces the mathematical values in describing control system by using the linguistic ambiguous labels for designing robust controllers. On the other hand, reinforcement learning, in particular Q-learning, shows good learning results in designing control input for performing constrained tasks by robots without knowing the system dynamics [22], [23]. The approaches of combining type-1 fuzzy logic and Q-learning for optimization of the consequence parts of fuzzy rules are promising due to the ease of implementation on mobile robot navigation [12]-[17] in which Q value is a cost for each navigation behavior. In this paper, we propose to combine Q-learning with interval type-2 fuzzy logic as an intelligent control for cost-based mobile robot navigation that yields smoother behaviors. The Q-learning algorithm is employed to evaluate and select the fuzzy rules for the mobile robot to take the action. The aim is to achieve a more smooth autonomous navigation of mobile robot in surveillance of unknown environment in which the mobile robot needs to be able to patrol a region and capture or follow one moving targets. Section 2 presents some related work. Section 3 introduces the intelligent control for cost-based mobile robot navigation based on fuzzy Q-learning. Validation of the intelligent control in simulation and real robot experiment for boundary following is shown in Section 4 and 5, respectively. Conclusion and future work is in Section 6.

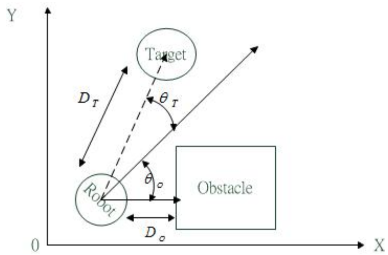

Fig. 1. The line of sight for target tracking and obstacles avoidance

2 Related Works

Moving target tracking/following and capturing is an on-line process. It is important in surveillance, and it has received increasing attentions more recently [1], [4]-[8].One task for the intelligent control of a mobile robot in this study is moving target tracking or capturing and obstacles avoidance. It is assumed that the target moves along a trajectory that is either well-defined and known a priori or unknown. Refer to Fig. 3.The control objective for the mobile robot is to controlling the orientation angle θ_0 and speed to guarantee that the mobile robot can follow the direction of the target, i.e. the real target orientation $\theta_T(t) \to 0$, and $D_T(t) \le d$ where d is a threshold (zero for capturing, nonzero for tracking) for the relative distance between the mobile robot and the moving target.

In [1], a potential field method was developed for velocity planning of a mobile robot to track a moving target in the presence of moving obstacles. In [4], using velocity vectors of the robot relative to each obstacle, an online navigation method based on calculating the best feasible direction close to an optimal direction to the target is proposed for pursuing a moving target amidst dynamic and static obstacles. Adaptive learning control for pursuit-evasion were presented in [6], [7], and experiments on capturing a moving object using pure pursuit were shown in [8].

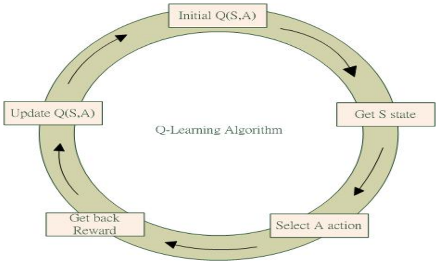

Fig. 2. The computation flowchart of Q-learning algorithm

3 Architecture Description of Fuzzy Q -Learning

3.1 Q-Learning Algorithm

Reinforcement learning is a promising approach to deal with control of physical robot with ever increasing complexity of hardware [22], [23] through experience and observations. Q-learning algorithm is a popular model-free reinforcement learning that have been demonstrated to give good results for some instances of robot tasks over the years. Fig. 2 shows the flowchart of *Q*-learning algorithm for a mobile robot that interacts with its environment via perception and action. Q-learning works as follows. After taking each action A_t from the action set *A* in a perceived state S_t of state space *S*, the mobile robot gets an immediate reward R_t at time *t* from the interaction with its surrounding environment, and changes its current state. Let the action-value function $Q(S_t, A_t)$ denote the *Q*-value for a state-action pair (S_t, A_t). Without knowing the dynamics of mobile robot being controlled, by measuring and storing the data (S_t, S_{t+1}, R_t) for taking the action A_t, the expected *Q*-value for a state-action pair is online updated as follows:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_t + \gamma \max_A Q(S_{t+1}, A_t) - Q(S_t, A_t)\right] \tag{1}$$

where the parameter $\alpha \in [0,1]$ denotes the learning rate, and the parameter $\gamma \in [0,1]$ denotes the discount factor that influences the current value of future reward. After a sufficient number of trials over time, the mobile robot tends to consistently learn a policy that maps the state to the action with maximum Q-value that will optimize the future reinforcement, independent of how the mobile robot behaves during the learning phase.

3.2 Fuzzy System

1) Traditional (Type1) Fuzzy System: Firstly, we design a fuzzy rule base of target pursuit and obstacles avoidance. In our work, the nearby environment information is obtained from a laser range finder. The sensing input data of nearby environment that measures the existence or closeness of obstacles or moving target within the field of view of the mobile robot is employed to control robot actions. The angular span of the sensing range from a laser range finder is partitioned into five segments in angular direction and three ranges in radial direction, as shown in Fig. 3. In Fig. 3, five directions are: R, L, F denotes right, left, in front of forward respectively; FL denotes in front of left, FR denotes in front of right. Three ranges of distance are: F denotes far distance, M denotes moderate distance and N denotes near distance.

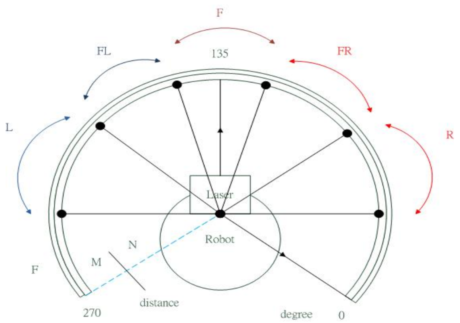

Fig. 3. The partition of field of view from a laser range finder for fuzzy system input

2) Interval Type-2 Fuzzy Logic System: An interval type-2 fuzzy set $\tilde{A}$, as shown in Fig4, is defined by a fuzzy membership function

$$\tilde{A} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \forall x \in X, \forall u \in J_x \subseteq [0,1]\} \quad (2)$$

where J_x denotes primary membership of x, $\mu_{\tilde{A}}(x,u) = \int_{u \in J_x \subseteq [0,1]} 1/u$ is the third dimension denoting a traditional (type-1) fuzzy set. It is completely described by its upper and lower membership functions denoted by

$\bar{\mu}_{\tilde{A}}(x) = \overline{FOU(\tilde{A})}$, $\underline{\mu}_{\tilde{A}}(x) = \underline{FOU(\tilde{A})}$,

respectively. The area between the upper membership function and lower membership function is called the footprint of uncertainty (FOU) of interval type 2 fuzzy set FOU provides an additional degree of freedom to handle uncertainties. The output of the inference will obtain a type-2 fuzzy set. The inference result is type-reduced to a

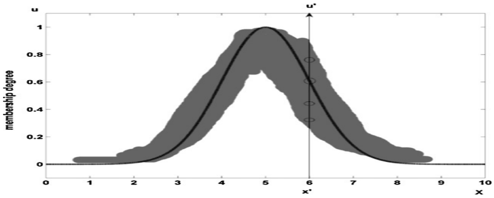

Fig. 4. FOU (shaded area) for an interval type-2 fuzzy set [15]

$$FOU(\tilde{A}) = \bigcup_{\forall x \in X} (\overline{\mu}_{\tilde{A}}(x), \underline{\mu}_{\tilde{A}}(x)) \tag{3}$$

type-1 fuzzy set, and the resulting type-reduced set is then defuzzified to generate a crisp output. In [19], both type-2 fuzzy and type-1 fuzzy were applied to speed control and the angle control of mobile robot and demonstrated that the performance of type-2 fuzzy system is much better than type-1 fuzzy system. For illustration, we design a two- input one-output fuzzy system shown in Fig. 5. The input data is provided by a laser range finder to detect environment information, and the output is a suitable value for the mobile robot to control the course. In this simulation study, the output set is segmented into five parts: large left, left, forward, right, and large right, respectively. The comparative performance of type-1 and interval type-2 fuzzy controllers is shown in Fig. 6. As shown in Fig. 6, the interval type-2 fuzzy controller shows better and smooth performance. The result of simulations encourages the use of interval type-2 fuzzy control as the main controller for the robot navigation task from the practical performance standpoint.

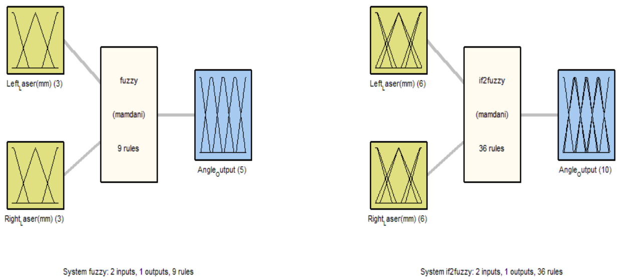

Fig. 5. Two- input one- output fuzzy system: type1 (left) vs type-2(right). Triangle or trapezoid membership functions of distance are used. Numerals in parenthesis denotes the number of rules.

3.3 Integrated Intelligent Control System

Fuzzy Q-learning has been applied to mobile robot navigation [15]-[17], where a reinforcement learning algorithm is used to fine tune the fuzzy rule base parameters.

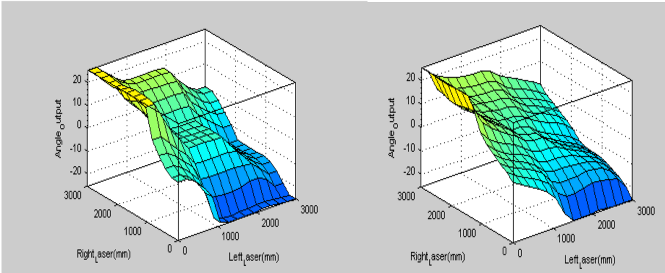

Fig. 6. The output surface of type-1 fuzzy (left figure) vs. interval type-2 fuzzy (right figure) controllers. x, y are distance in the right and left directions, respectively; z is the output of robot turning angle.

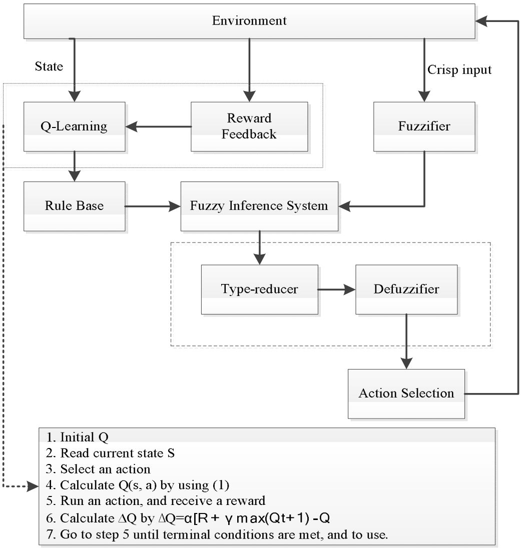

Fig. 7. The structure of integrating Q-learning with an interval type-2fuzzy controller

Fig. 7 shows the flow chart of integrating Q-learning algorithm into interval type 2 fuzzy controller. An interval type 2 fuzzy system is characterized by IF-THEN rules, where their antecedent or consequent sets are of interval type 2. The type 2 fuzzy logic system includes a fuzzifizer, a rule base, fuzzy inference engine, and output processor. The output processor includes a type-reducer and a defuzzifier and it generates a type 1 fuzzy set output. The integration allows the fuzzy rule to be evaluated by the Q-learning so that for more complex situation defined by fuzzy rules, the Q values could be provided as the cost to individual rules that are activated by current state-action pair. Here the rule is in the form of

IF S is s THEN a is A with $Q(s,A)$

where the state and action membership functions are given as interval type 2, and thus $Q(s,A)$ has two values, one for each membership function. Each rule for control is associated with a Q-value after learning results to show the goodness of the rule. An illustration is shown in Table1 for Fig. 5 where there are five fuzzy sets of the rule base in A: Large Left, Left, Forward, Right, and Large Right.

3.4 Kalman Filter

To estimate the target's expected movement variation in the speed and position, we incorporate the Kalman filter to probabilistic estimate of its motion [18]. The Kalman and it can refer to figures 10 and 14filter is very powerful in estimations of past, present, and even future state, and it can do so even when the precise nature of the modeled system in unknown. The filter estimates a process by using a form of feedback control. The filter estimates the process state at some time and then obtains feedback in form of measurements. The time update equations can also be thought of as predictor equations, while the measurement update equations can be thought of as corrector equations as shown in Fig. 8. The time update projects the current state estimate ahead in time. The measurement update adjusts the projected estimate by an actual measurement at that time. The well-known equations for the time and measurement updates are repeated in Table 2 and Table 3 for easy reference. The matrix A relates the state at previous time step $k-1$ to the state at the current step k, and the matrix B relates the control input u to the state x. The process noise covariance Q and measurement noise covariance R matrices might change with each time step. The matrix H relates the state to the measurement z_k with normal probability distribution.

Table 1. Fuzzy Rule Base

Rule Base		Left Laser		
		Near	Medium	Far
Right Laser	Near	$A_1\ with\ q_{11}, q_{12}$	$A_2\ with\ q_{21}, q_{22}$	$A_3\ with\ q_{31}, q_{32}$
	Medium	$A_4\ with\ q_{41}, q_{42}$	$A_5\ with\ q_{51}, q_{52}$	$A_6\ with\ q_{61}, q_{62}$
	Far	$A_7\ with\ q_{71}, q_{72}$	$A_8\ with\ q_{81}, q_{82}$	$A_9\ with\ q_{91}, q_{92}$

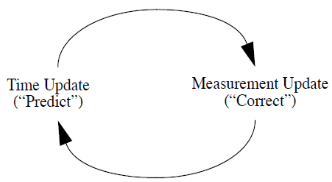

Fig. 8. The ongoing discrete Kalman filter cycle [18]

Table 2. Discrete Kalman Filter Time Update Equations

DISCRETE KALMAN FILTER TIME UPDATE EQUATIONS	
$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1}$ $P_k^- = AP_{k-1}A^T + Q$	(4)

Table 3. Discrete Kalman Filter Measurement Update Equations

DISCRETE KALMAN FILTER MEASUREMENT UPDATE EQUATIONS	
$K_k = P_k^- H^T (HP_k^- H^T + R)^{-1}$ $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$ $P_k = (I - K_k H)P_k^-$	(5)

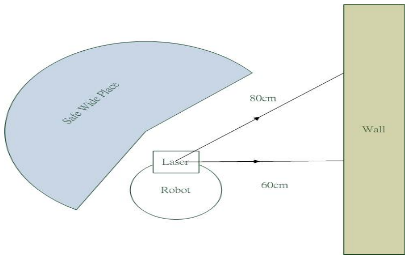

Fig. 9. A simple environment for the task of wall following

4 Simulation

4.1 Wall-Following in a Simple Environment

Evolutionary aspect of Q-learning is better understood by observing the motion of mobile robots [2]. Here we perform an off-line Q-learning simulation of a right wall following mission [12], [20], [21] by keeping a safety distance with a wall, in which the static wall is on the right, and a safe wide place is on the left of the robot as shown in Fig.9. The robot state is described by two extreme points sensed by the laser range finder: the rightmost and extreme right front. The robot motion is described by a sequence of action {turning right, turning left, turning zero} without stopping. For each state sensed by the readings from a laser range finder, an action executed by the mobile robot will cause a cost (in our case, the acquired Q value, 0 for collision, 50 for collision-free and 100 for wall following) given by the interaction with the environment. After the convergence of Q-learning as shown in Fig. 10, the cost-based navigation behavior corresponding to the maximum Q value shown in Q- table of Table 4 is selected to execute in each moving step of mobile robot. In this simulation, being informed of the Q value, the robot will consider the action for next step as turning zero to achieve the best performance. This demonstrates that the navigation based on Q-learning is promising for real-world implementation, since the robot is able to learn the desired reactive behavior in this simple situation.

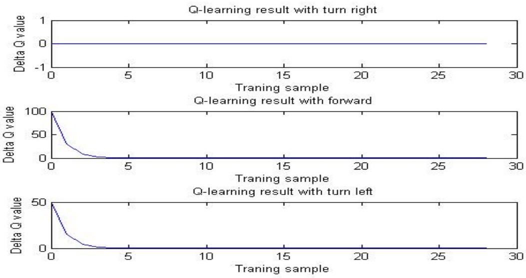

Fig. 10. The results of after learning

Table 4. Fuzzy Q-learning

action	Turning Right	Turning Zero	Turning Left
Learned max Q-Value	0	142.8478	71.4130

4.2 Kalman Filter for Estimation of Target

This section describes the task of pursuit of a one-dimensional moving target by a mobile robot. The robot has onboard sensors that continuously locate the moving target. A pure pursuit is one way to specify how to do repetitive new course calculations: target update based on look ahead distance [8]. A simulation of pure pursuit for one-dimensional moving point target is shown in Fig. 11 where a capture occurs if the point robot and the point target occupy the same place at the same time. The target is simply moving in one direction (right to left) with known moving trajectory and the point robot can arrest the target using pure pursuit method. To minimize the time of capturing the target, the robot moves at its maximum speed

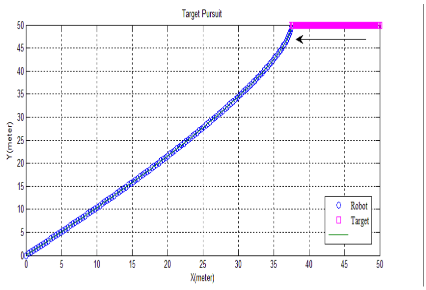

Fig. 11. The simulation of pure pursuit where the moving target moves along a fixed horizontal direction

$V_R \geq V_T$, where the maximum speed of the target is V_T.However, in situations which the target moves at an unfixed direction of travel and unknown velocity on a domain, even randomly such as Markov chain or Brownian motion, the robot needs to predict the unknown target motion for achieving a higher possibility of eventually capturing the target. Therefore, we employ the Kalman filter method [18] to solve this problem, assuming the target movement is changed randomly, and the Kalman filter is used to estimate next state to build a suitable trajectory as shown in Fig. 12 so that the method of pure pursuit could be applied to the estimated trajectory.

5 Experimental Results

In this section, an experiment is conducted which the robot is operating for patrol in an unknown, unstructured environment. In addition to avoid the obstacles for safe navigation, the mobile robot is required to explore and then patrol by right wall following in an unknown environment. Wall following by a mobile robot has been

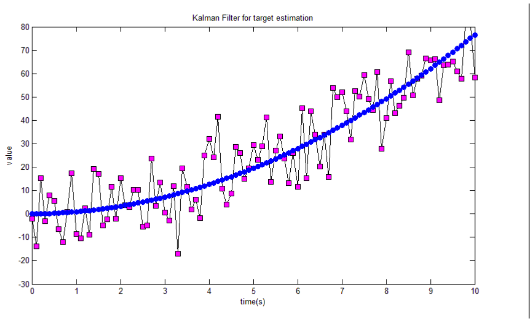

Fig. 12. Simulation of the Kalman filter for target estimation. Red dots denote the real movements of the target that moves randomly within a range. Solid blue curve denotes the estimated trajectory.

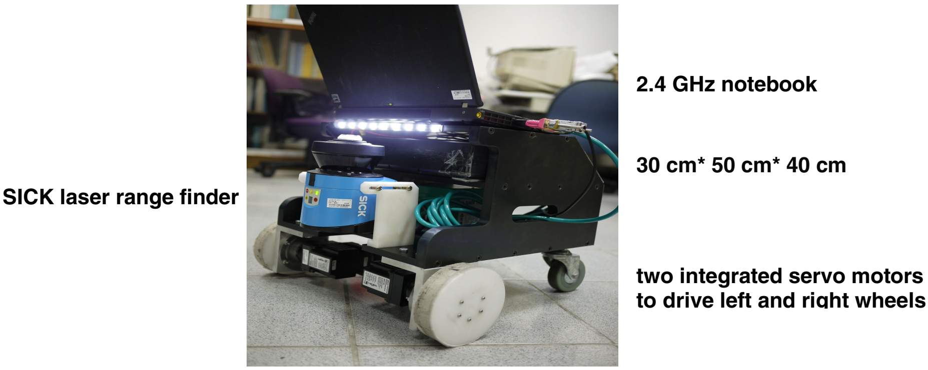

Fig. 13. The wheeled mobile robot equipped with a laser range finder for experimrnt

tested using proximity sensors (sonar or infrared) for different control algorithms [12], [20], [21] based on line of sight range measurements (distance and its rate), and/or bearing angle. Here our implementation and testing is conducted on a mobile robot equipped with a SICK laser range finder in the front, as shown in Fig. 13, to perform a scan of 180 degrees of field of view with maximum sensing range 5m to obtain nearby environment information. We employed the interval type-2 fuzzy Q-learning techniques for obstacles avoidance and wall following in an unknown environment. In this task, the robot needs to explore and follow the right wall, while avoiding the obstacles. This task spends 125 seconds of total time for a completion of the patrol, in which a feedback is provided every 0.3 seconds. The patrol trajectory and the output of turning angle are shown in Fig. 14 and Fig. 15, respectively. In Fig. 15, the fluctuation of output angle indicates that the mobile robot encountered flat real walls or curved obstacle boundaries to make a fine tuning of its motion direction, therefore the output response is seen a substantial beating as the mobile robot encounters a corner. The patrolling in a real indoor environment is shown in Fig. 16 (http://youtu.be/es93QfFz8qs).

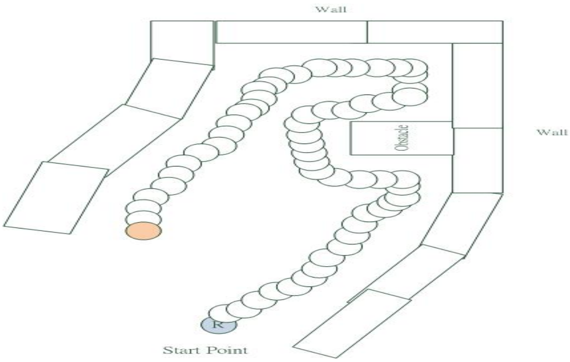

Fig. 14. The patrolling trajectory in the experiment

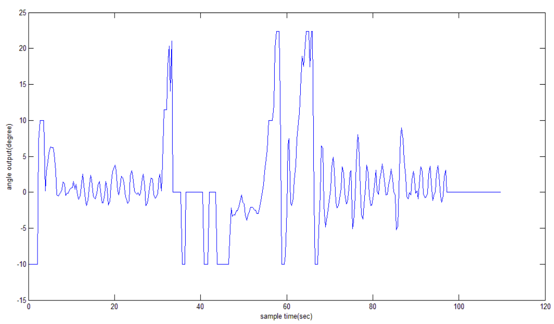

Fig. 15. The turning angle that the mobile robot approaches the wall

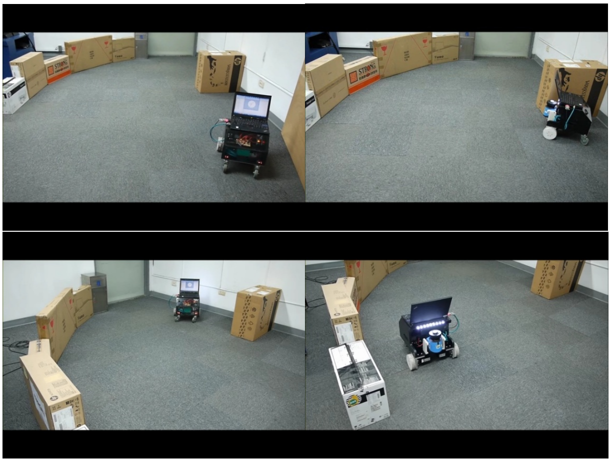

Fig. 16. The snapshots of patrolling experiment in a real environment (from the left upper photo to right bottom photo)

6 Conclusion

In this paper, we proposed a novel autonomous and intelligent controller for mobile robot navigation tasks in surveillance which requires the accomplishment of a variety of missions. The system is composed of reinforcement learning, fuzzy control, and a prediction component based on Kalman filter for estimating the trajectory of moving target to support a mobile robot for target pursuit, obstacles avoidance, and wall following of patrolling mission. The controller is composed by fuzzy Q-learning where the fuzzy rules are selected by the Q learning to meet a diverse set of navigation tasks in surveillance. The interval type-2 fuzzy logic system is employed, which shows better and smooth navigation performance. For tasks of moving object such as pursuit- evasion, the Kalman filter could be employed for a randomly moving target to predict its motion trajectory. Preliminary experiment in a simple real and unknown indoor environment validates that the intelligent control is effective to learn from the data collected and accomplish the tasks of wall following and obstacle avoidance. Ongoing and future work are planned to improve the current implementation of intelligent control for more complex mobile robot navigation behaviors such as capturing a moving target. For improving the generalization capability of reinforcement learning, future work will consider enhancing the computational efficiency using adaptive learning algorithm for navigation in more complex environment.

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