An ART-Based Fuzzy Controller for the Adaptive Navigation of a Quadruped Robot

Xuedong Chen, Keigo Watanabe, *Member, IEEE*, Kazuo Kiguchi, *Member, IEEE*, and Kiyotaka Izumi, *Member, IEEE*

***Abstract*—An adaptive-resonance theory (ART)-based fuzzy controller is presented for the adaptive navigation of a quadruped robot in cluttered environments, by incorporating the capability of ART in stable category recognition into fuzzy-logic control for selecting the adequate rule base. The environment category and the navigation mechanism are first described for the quadruped robot. The ART-based fuzzy controller, including an ART-based environment recognizer, a comparer, combined rule bases, and a fuzzy inferring mechanism, is next introduced for the purpose of the adaptive navigation of the quadruped robot. Unlike classical/conventional adaptive-fuzzy controllers, the present adaptive-control scheme is implemented by the adaptive selection of fuzzy-rule base in response to changes of the robot environment, which can be categorized and recognized by the proposed environment recognizer. The results of simulation and experiment show that the adaptive-fuzzy controller is effective.**

***Index Terms*—Adaptive control, adaptive-resonance theory (ART), fuzzy controller, navigation, obstacle avoidance, quadruped robot.**

I. INTRODUCTION

As ONE TYPE of legged vehicles, quadruped robots can perform some tasks in the work space with a rough terrain, e.g., mapping building on the uneven ground, searching and removing landmine, collecting volcano data, etc. The autonomous walking of a quadruped robot depends on not only the gait implementation but also the navigation control. Although there are a lot of works published on gait generation and control for quadruped robots [1]–[17], to the best of our knowledge, few papers are found addressing the adaptive navigation of a quadruped robot in cluttered environments up to now. For example, Lee and Song [1] described the gait generation method for a quadruped robot to follow a planned trajectory in a known obstacle-strewn environment. Ito *et al.* [17] discussed the adaptive gait pattern of a quadruped robot to a treadmill environment (ground profile) rather than an adaptive navigation in a walking space. Furthermore, it is very difficult or complicated to estimate robot position in a complex environment for the navigation control by means of the existing algorithms of gait generation. On the other hand, many researchers investigated navigation and path planning of mobile robots [18]–[27], [42]–[45]. For instance, Taylor and Kriegman [22] provided exploration and navigation algorithms that would enable a mobile robot equipped with a vision-based recognition system to carry out an exploration of its environment in search of one or more recognizable objects. Yamamoto *et al.* [43] developed a sensor-based navigation system using a target direction sensor for mobile robots. Okada *et al.* [42] described a human–robot cooperation system which could realize robust behaviors of mobile robots in a real world by combining human ability of recognition, inference and decision with robot's autonomy. In addition, Kubota *et al.* [18] introduced behavior learning of human-friendly robots by human symbolic teaching for navigation of the mobile robots.

In this paper, we attempt to develop an adaptive-fuzzy controller to navigate a quadruped robot based on classification and recognition of environment. Unlike mobile robots, quadruped robots are able to walk on extremely irregular ground profile and to step on/over some convex/concave objects which are regarded as the obstacles mobile robots have to avoid. Although there have been some creative outcomes of vision system which could be used to observe environment for navigation of mobile robots [22], [44], [45], it is still difficult to classify and recognize field environments by means of the existing vision/sensor systems for navigation of quadruped robots to perform hazardous tasks. In particular, there is a lack of a widely practical and reliable vision system to identify various terrains and obstacles that quadruped robots cannot step on/over. As a result, conventional sensors cannot give full play to measure distances between a robot and these terrains/obstacles. Therefore, human involvement is necessary to describe the complex environment for the navigation of the robot. In order to lighten human load, to develop the robot's autonomy, and finally to implement the completely autonomous navigation by means of a sophisticated vision/sensor system, the adaptive-fuzzy controller is designed in such a way that it can obtain the inputs from fuzzy language or environment database provided by a human operator in a faraway observation.

Classical fuzzy adaptive-control methods have two kinds approaches: one is the learning model (LMAC) and the other is the model reference adaptive control (MRAC). It is well-known that, unfortunately, real-time control is difficult due to the long computational time and the design and implementation of these controllers are difficult due to their complex mathematical structure. Conventional fuzzy-adaptive controllers are designed so that membership functions are modified by some parametric changes of the system. However, this method leads to an ineffectual robust property of the fuzzy controller [29]. Moreover, it makes a lookup table method impossible and generates the

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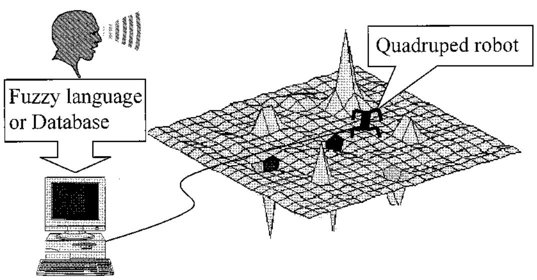

Fig. 1. Human-coexistent quadruped robot system.

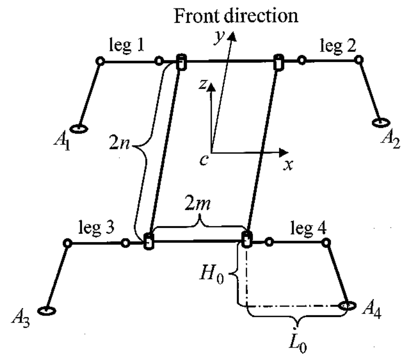

Fig. 2. Schematical drawing of the quadruped robot TITAN-VIII.

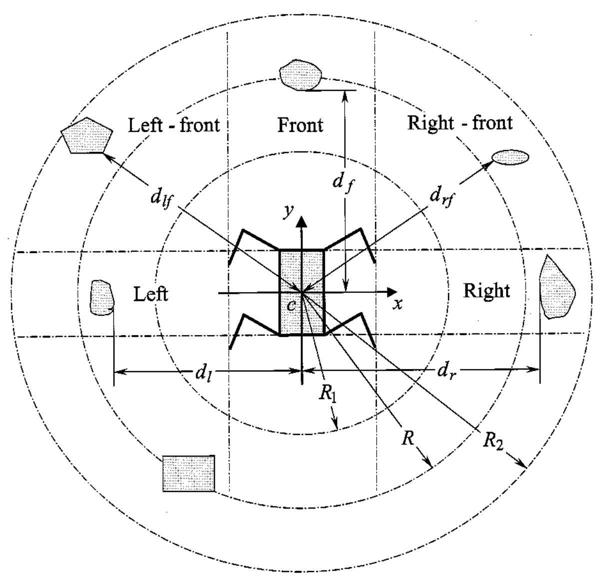

Fig. 3. Environment definition and division, where the shaded areas denote obstacles that the robot cannot step on/over.

same problems as in classical adaptive-control methods [28]. Actually, such an adaptive control can be also implemented by an adaptive selection of fuzzy rule. For example, Kim *et al.* [29] presented a fuzzy controller constructed with parallel combination of robust controllers by using a multirule-base architecture, and verified the robust stability of the fuzzy controller even in a big parametric uncertainty. Nevertheless, an online identification of the parametric variations of the controlled system is a difficult and unavoidable problem. Clearly, classification and recognition of environmental changes is a key technique to realize the adaptive navigation of a quadruped robot.

Adaptive-resonance theory (ART) [30]–[33] is known to be powerful in self-organization of stable category recognition. The reason is that ART networks and algorithms maintain the plasticity required learning new patterns, while preventing the modification of patterns that have been learned previously. Although many people have found the theory difficult to understand, this capability has stimulated a great deal of interest. For example, Lin *et al.* [35], [36] performed an online structure/parameter learning algorithm by combining the back-propagation learning scheme for parameter learning with the fuzzy ART algorithm for structure learning. We here propose an ART-based fuzzy-adaptive controller by incorporating the capability of ART in stable category recognition into the fuzzy-logic control for selecting the adequate rule base. The proposed approach is characterized by quickly recognizing the current environment category using an ART-based neural network, and by implementing an adaptive selection of fuzzy-rule base in response to changes of environment.

The rest of the paper is organized as follows. The environment category and the robot navigation are presented in Section II. Section III motivates and describes the design of the adaptive navigation controller. Section IV shows the simulation and experimental results. Finally, Section V discusses some of conclusions drawn from this research.

II. Environment Category and Navigation Mechanism

A. Environment Category

A human-coexistent quadruped robot system is schematically shown in Fig. 1. The basic mechanism of the quadruped robot named TITAN-VIII is drawn in Fig. 2, where $2m$ and $2n$ denote the size of robot body, while L_0 and H_0 represent the initial leg stretch in horizontal and vertical respectively. As shown in Fig. 3, we define the environment of the quadruped robot to be the area surrounding the robot with a radius R centered at the robot. The radius R is an important parameter for the environment cognition because the environment scope is relative to walking specifications of robot, which leads to different environment category. For example, if $R = R_I$ in Fig. 3, the environment of the robot is the nonobstacle one; but if $R = R_2$ in Fig. 3, then the environment of the robot is the obstacle-strewn one. Actually, R is naturally embodied in a changeable variable if obstacle distances are provided in fuzzy language. On the other hand, the environment category also depends on obstacle distribution in the specified environment with respect to the robot. Therefore, the environment category may vary with the position of the robot in the environment. As a simple example shown in Fig. 4, the obstacle is in the front of the robot drawn in solid line, whereas it is in the right of the robot drawn in dotted line, and clearly, the environment category of the former should be different from that of the latter. Moreover, categorizing the environment also depends on the division of the environment with respect to the robot [19]. As shown in Fig. 3, we consider five subareas of the environment with respect to the robot: front, left, right, left-front, and right-front, where d_f, d_l, d_r, d_{lf}, and d_{rf} denote the obstacle distances in the corresponding subareas, respectively. Therefore, there exist 32 pos-

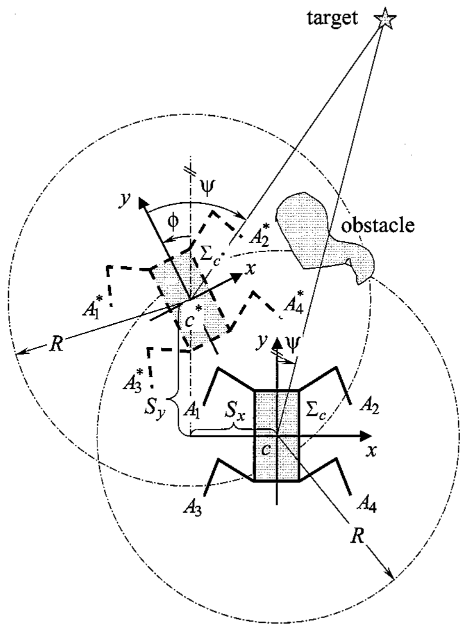

Fig. 4. Robot is navigated to a specified target with the obstacle avoidance, where the robot in solid line denotes the current posture and that in dotted line represents the next posture after a gait cycle.

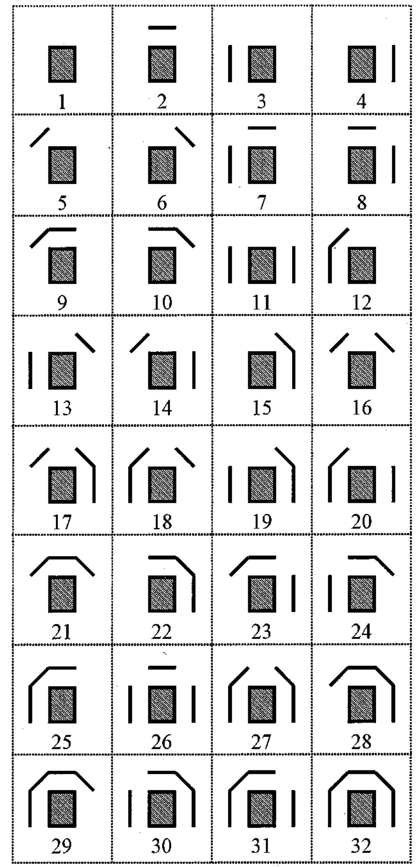

Fig. 5. Categories of environment for a quadruped robot, where the rectangles denote the robot and the line segments denote obstacles.

sible environment categories shown in Fig. 5 under the circumstances. The obstacle distances are evaluated according to the current robot posture (position and orientation) and the environment database, or are directly provided in linguistic variables such as *Very Near*, *Near*, *Middle*, *Far*, *Very Far*, etc.

B. Navigation Mechanism

The quadruped robot realizes its travel in stepping locomotion mechanism. In our previous work [47], the control algorithm of an omnidirectional crawl has been proposed and implemented for the robot TITAN-VIII on the irregular ground. Based on a prescribed walking requirements including robot stride and turning angle in one step (a gait cycle), the quadruped robot can be controlled to perform the gait cycle with a desired stride, denoted by S, and a desired turning angle, represented by ϕ. In other words, given a command on the desired stride and turning angle in a gait cycle, the robot can be navigated. As shown in Fig. 4, the robot crawls toward the specified target without collision with the obstacle, where $\Sigma_c(c - xyz)$ denotes the body frame and ψ represents the target-orientation angle. According to the current environment, the robot performs a gait cycle to reach the posture in dotted line for the obstacle-avoidance. Here, $\Sigma_{c^*}(c^* - xyz)$ denotes the body frame after the gait cycle, S_x and S_y denote the components of the stride S in x- and y-directions of Σ_c, A_i for $i = 1, 2, 3$, and 4 represent the current footholds of the robot, and A_i^* for $i = 1, 2, 3$, and 4 represent the next footholds of the robot. The generalized gait generation is described as follows.

Drawing inspiration from the reptile crawl, we designed the omnidirectional gait pattern for TITAN-VIII [47], which mainly includes determination of the footholds and selection of the sequence of swing leg. A gait cycle is defined as a successive performance (*lift up–swing ahead–put down*) for four legs of the quadruped robot, in which the robot is controlled to begin at the initial posture and to end up at the next initial posture. The so-called initial posture of the robot is given in Fig. 2, where the initial leg stretch in horizontal is L_0, whereas the actual leg stretch in vertical is subject to the roughness of ground profile. Therefore, once the robot performs a gait cycle, it returns to the initial posture for the next gait cycle. The next footholds of the robot with respect to the current body frame Σ_c are expressed by ${}^c\boldsymbol{p}_{A_i^*} = [{}^cx_{ai}^* \; {}^cy_{ai}^* \; {}^cz_{ai}^*]^T$ for $i = 1, 2, 3$, and 4. The orientation matrix of Σ_{c^*}, with respect to Σ_c, is denoted by ${}^c\mathbf{R}_{c^*}$, i.e.

$$
{}^c\mathbf{R}_{c^*} = \begin{bmatrix} \cos\phi & -\sin\phi & 0 \\ \sin\phi & \cos\phi & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{1}
$$

Thus, we have

$$
{}^c\boldsymbol{p}_{A_i^*} = {}^c\boldsymbol{p}_{c^*} + {}^c\mathbf{R}_{c^*} \, {}^{c^*}\boldsymbol{p}_{A_i^*} \tag{2}
$$

where ${}^c\boldsymbol{p}_{c^*}$ denotes the stride vector of the robot in the gait cycle with respect to the current body frame Σ_c, and ${}^{c^*}\boldsymbol{p}_{A_i^*}$ represents the initial position of the ith foot with respect to the body frame. From Figs. 2 and 4, it follows that

$$
{}^c\boldsymbol{p}_{c^*} = [S_x \; S_y \; S_z]^T \tag{3}
$$

$$
{}^{c^*}\boldsymbol{p}_{A_i^*} = [\delta_1(m + L_0) \quad \delta_2 n \quad {}^cz_{ai}^* - S_z] \tag{4}
$$

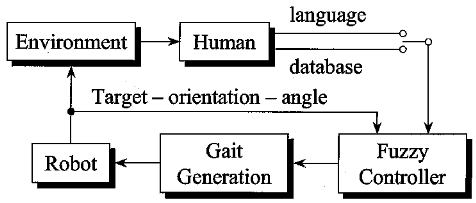

Fig. 6. Flow diagram of the navigation control for the quadruped robot.

where $\delta_1 = 1$ for $i = 2$ or 4, $\delta_1 = -1$ for $i = 1$ or 3, $\delta_2 = 1$ for $i = 1$ or 2, and $\delta_2 = -1$ for $i = 3$ or 4. Therefore, we can finally obtain

$$^{c}\boldsymbol{p}_{A_i^*} = \begin{bmatrix} S_x + \delta_1(m + L_0)\cos\phi - \delta_2 n \sin\phi \\ S_y + \delta_1(m + L_0)\sin\phi + \delta_2 n \cos\phi \\ {}^{c}z_{ai}^{*} \end{bmatrix}. \quad (5)$$

Selection of the sequence of swing leg in a gait cycle must abide by the following rules.

- Each leg only works as the swing leg once a gait cycle.
- The robot must be statically stable in any time.
- The leg stretch does not exceed its limit to reach the desired foothold.
- The leg with smaller stretch should be selected as the swing leg if there are two possible selections.

In fact, the quadruped robot can also realize an omnidirectional walking through straight-going gait and standstill-turning gait. The former is given with $\phi = 0$, $S_x = S_z = 0$, and $S_y \neq 0$; while the latter is given with $S_x = S_y = S_z = 0$ and $\phi \neq 0$. In other words, when the robot needs to take a turning for an obstacle-avoidance or an adjustment in direction, it adopts the standstill-turning gait; otherwise it makes the straight-going gait with great strides toward a specified target. Therefore, the robot navigation is concentrated on providing a command of turning angle to the quadruped robot at a gait cycle. The following mission is to design an adaptive-fuzzy controller that it can provide the navigation command to the robot gait generation/control system [47] based on the recognition of the current environment category.

III. Adaptive Fuzzy Controller Design

Fig. 6 presents the flow diagram of the navigation control of the quadruped robot. A human operator can provide the environment information to the fuzzy controller in either case: fuzzy language and database. The former implies that the current obstacle distances in five subareas are directly given in the following linguistic variables: *Very Far (VF), Far (FA), Middle (MI), Near (NE),* and *Very Near (VN)*. The latter means that the human operator gives environment database to the fuzzy controller from an observation or map of the environment, and the obstacle distances are evaluated according to the database and the current robot posture. In addition, the target-orientation angle is also evaluated according to the current robot posture and the specified target position. The output of the fuzzy controller is a turning angle. As a result of the control, the robot performs a standstill-turning gait with the desired turning angle, whereas the robot takes a straight-going gait with a stable stride when the control output is zero.

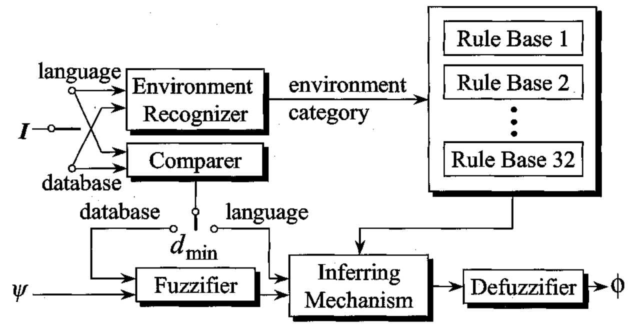

Fig. 7. Block diagram of the adaptive-fuzzy controller.

Owing to the complexity of environment, it is very difficult to constitute such an adequate rule base that the fuzzy controller possesses a wide robustness to various cases in the complex environment. In order to solve the problem, Wu [27] made an attempt to propose a learning fuzzy algorithm similar to "simulated annealing" method to implement fuzzy rules, which increases the flexibility in determining the range parameters of the fuzzy rules and tends to find a navigation path with global minimum distance, but considerably increases the computation burden and makes the choice of the nominal values of the range parameters more difficult. Based on the above work in Section II, in fact, any complex environments can be properly categorized to meet such needs that the adequate fuzzy rules can be respectively designed for each environment category according to expert knowledge. Each environment category corresponds to an individual fuzzy-rule base, which enables the controller to have a robust stability in the specified environment category. Combining these individual rule bases in parallel, we propose a fuzzy controller which implements its adaptive property by online recognition of current environment category for the robot then selection of the corresponding rule base to make a fuzzy inference. The structure of the fuzzy controller is shown in Fig. 7, which is composed of an environment recognizer, a comparer, combined rule bases, fuzzifier, a fuzzy inferring mechanism, and a defuzzifier. The comparer performs a comparison among the obstacle distances for the minimum one, which is called the critical obstacle distance $d_{\min}$. For the database case, the critical obstacle distance is expressed by

$$d_{\min} = \min\{d_f,\, d_l,\, d_r,\, d_{lf},\, d_{rf}\} \quad (6)$$

whereas the critical obstacle distance is directly expressed in a linguistic variable for the case of fuzzy language. The control strategy is as follows: first, the current environment category is recognized by the environment recognizer according to the environment radius and the obstacle distances; then, the fuzzy-rule base is selected in response to the current environment category; finally, the fuzzy inferring mechanism makes an inference from the fuzzy inputs of the target-orientation angle and the critical obstacle distance to obtain the crisp output of a turning angle through defuzzification.

A. ART-Based Environment Recognizer

The environment recognition in the control loop is implemented in the form of the ART-II neural network [31]. The

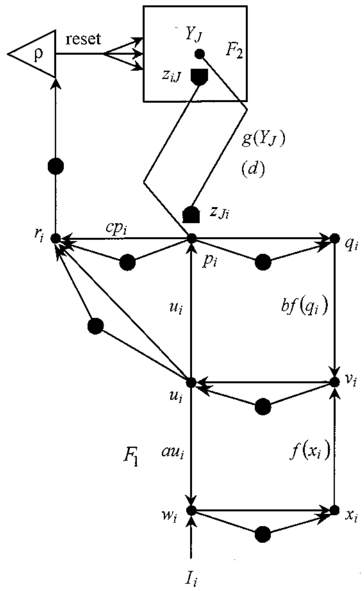

Fig. 8. Network topology of ART-II.

ART-II is a member of the class of adaptive-resonance architectures that is designed to handle both binary and analog patterns and is a modification over the first proposed ART architecture called ART-I [30]. Fig. 8 depicts the ART-II network topology. This network includes the principal components of all ART modules, namely an attentional subsystem, which contains an input representation field F_1 and a category representation field F_2, and an orienting subsystem, which interacts with the attentional subsystem to carry out an internally controlled search process. The two fields are linked by both a bottom-up $F_1 \rightarrow F_2$ adaptive filter and a top-down $F_2 \rightarrow F_1$ adaptive filter. A path from the ith F_1 node to the jth F_2 node contains a long term memory (LTM) trace, or adaptive weight z_{ij}, a path from the jth F_2 node to the ith F_1 node contains a weight z_{ji}. These weights gate, or multiply, path signals between fields. See the reference [31] for the ART-II system dynamics. The basic mathematical relationships in Fig. 8 are listed as follows:

$$p_i = u_i + \sum_j g(y_j) z_{ji} \tag{7}$$

$$q_i = \frac{p_i}{e + |\boldsymbol{p}|} \tag{8}$$

$$u_i = \frac{v_i}{e + |\boldsymbol{v}|} \tag{9}$$

$$v_i = f(x_i) + bf(q_i) \tag{10}$$

$$w_i = I_i + au_i \tag{11}$$

$$x_i = \frac{w_i}{e + |\boldsymbol{w}|} \tag{12}$$

for $i = 1, \ldots, M$ and $j = 1, \ldots, N$, where M is the number of F_1 input channels; N is the number of nodes at stage F_2; the network parameters are such that $a = b = 10.0$, $c = 0.10$, $d = 0.9$, and $e = 0.0$; the threshold is $\theta = 1/\sqrt{M}$; and $|\boldsymbol{p}|$, $|\boldsymbol{v}|$, and $|\boldsymbol{w}|$ represent the L_2 norms of the vectors $\boldsymbol{p}$, $\boldsymbol{v}$, and $\boldsymbol{w}$, respectively. In addition, the thresholding function is adopted as follows:

$$f(t) = \begin{cases} 0, & \text{if } 0 \le t < \theta \\ t, & \text{if } t \ge \theta. \end{cases} \tag{13}$$

TABLE I
SOME TYPICAL TRAINING DATA OF THE ENVIRONMENT CATEGORY, WHERE I DENOTES THE LINGUISTIC CASE AND II REPRESENTS THE DATABASE CASE (IN METERS)

Category	d_f		d_l		d_r		d_{lf}		d_{rf}	
No.	I	II	I	II	I	II	I	II	I	II
1	1.00	2.00	1.00	2.00	1.00	2.00	1.00	2.00	1.00	2.00
	1.00	2.00	0.75	1.50	1.00	2.00	1.00	2.00	1.00	2.00
3	1.00	2.00	0.50	1.00	1.00	2.00	1.00	2.00	1.00	2.00
	1.00	2.00	0.25	0.50	1.00	2.00	1.00	2.00	1.00	2.00
	0.75	1.50	1.00	2.00	1.00	2.00	0.25	0.50	1.00	2.00
9	0.50	1.00	1.00	2.00	1.00	2.00	0.50	1.00	1.00	2.00
	0.25	0.50	1.00	2.00	1.00	2.00	0.75	1.50	1.00	2.00
	1.00	2.00	0.75	1.50	1.00	2.00	0.50	1.00	0.75	1.00
18	1.00	2.00	0.50	1.00	1.00	2.00	0.75	1.50	0.50	1.00
	1.00	2.00	0.25	0.50	1.00	2.00	0.25	0.50	0.25	0.50
	1.00	2.00	0.75	1.50	0.5	1.00	0.50	1.50	0.75	1.50
27	1.00	2.00	0.50	1.00	0.25	0.50	0.50	1.00	0.50	1.00
	1.00	2.00	0.25	0.50	0.00	0.50	0.75	1.50	0.25	0.50

The ART-II network is implemented on a digital computer. The network is used in the supervised learning mode and is trained offline before its inclusion into the control loop. The inputs of the network, $\boldsymbol{I} = [I_1 I_2 \cdots I_M]$, include R, d_f, d_l, d_r, d_{lf}, and d_{rf}. The output of the network is the environment category. Similarly, the input variables can be crisply inputted to the network in the database case, that is

$$\boldsymbol{I} = [R \; d_f \; d_l \; d_r \; d_{lf} \; d_{rf}] \tag{14}$$

where

$$d_t = \begin{cases} d_t, & \text{if } d_t < R \\ R, & \text{if } d_t \ge R \end{cases} \tag{15}$$

for $t = f, l, r, lf$, and rf. In addition, if there is no obstacle in some subarea, then the corresponding obstacle distance is regarded as an infinite. On the other hand, if the obstacle distances are given in the linguistic variables: VF, FA, MI, NE, and VN, these linguistic variables should be transformed into the numerical symbols, which also coincides with the fuzzy membership to be presented in the following section, that is

$$VF = 4 \quad FA = 2 \quad MI = 0 \quad NE = -2 \quad VN = -4.$$

Thus, the obstacle distances are inputted to the network in the following analogs:

$$I_i = 0.5 + \frac{Q_i}{8} \tag{16}$$

for $i = 2, 3, \ldots, 6$, where Q_i represents the numerical symbol of the corresponding obstacle distance. Note that, for the linguistic case, the environment radius R is embodied in the obstacle distances expressed by the linguistic variables, i.e., the environment scope is naturally limited in the *Very Far (VF)*, and hence, $I_1 = 1$ as the input of R under the circumstances.

The training data for the network is obtained from the real environment categorizing as shown in Fig. 5, which can be the analog quantity from (16) or the real physical quantity. The former describes the relative degree of the distance between robot and obstacle in nondimensional coefficient, and the latter denotes the real distance between robot and obstacle in meter. We adopt the typical-sample to establish the training data. For example, Table I lists some of typical training data for the first, third, ninth, 18th, and 27th categories, where I represents the linguistic case while II denotes the database case with the environment radius $R = 2$ m. In the concrete, 0.25, 0.5, 0.75, and 1 respectively denote the *Near, Middle, Far*, and *Very Far* as the typical-samples to present the existence of obstacle for the linguistic case (Case I), while the existence of obstacle within an environment with $R = 2.0$ m is typically expressed by physical obstacle distances such as 0.5, 1.0, 1.5, and 2.0 m for the database case (Case II).

Once the training data is available, the network is configured such that the number of nodes in the feature representation field F_1, which corresponds to the dimension of the input feature vector composed of the environment radius and five obstacle distances in present application, is fixed. The number of processing nodes in the category representation field F_2, is generally greater than the total number of input patterns in the prototype set. Each pattern in the prototype set is sequentially presented to the network once. A second cyclic presentation of the prototype set may be made for a stable category confirmation. Subsequent presentations do not alter the resulting category structure. The category structure represents the stable space partitioning of the neural network depending on the number of stable categories established during training and the different feature vectors that were classified into these categories. During training, the attentional vigilance parameter ρ is set at its highest value (0.99) to ensure a high resolution of the resulting category structure.

When the network is presented with a feature vector for the first time, it is encoded in the LTM through modification of the LTM connection weights. A node is allocated in the network's category representation field F_2 to represent the pattern. The parameters associated with the feature vector now get assigned to this allocated F_2 node. On presentation of subsequent feature vectors, the network's orienting subsystem first determines closeness of match between the pattern currently imposed on the network and any of the patterns that have previously been seen. Since the vigilance parameter is set high, a new node is allocated for the pattern. However, if the current pattern happens to be closely matched to the one that the network has already seen, it is clustered into the same category. It is, therefore, possible to partition the network's state space so that each partition serves as an attractor for a particular type of response characterized by its feature vector. The vigilance parameter helps to control the coarseness or fineness of classification desired. After completion of training, the top-down and the bottom-up connection weights of the network, along with the network parameters, are saved into the computer memory. The above process is repeated for different sets of values of the obstacle distances. After its inclusion into the control loop, the trained network can realize the rapid recognition of the environment category shown in Fig. 5, according to the obstacle distances evaluated from the environment database or directly provided in linguistic variables.

B. Fuzzy Reasoning

1) Fuzzification: The fuzzy inferring mechanism accepts the fuzzy input. Before the data can be fuzzified, it should be normalized to meet the range of the universe of discourse suitable for the controller input. In the proposed fuzzy controller, the target-orientation angle ψ and the turning angle ϕ also need to be fuzzified in addition to the critical obstacle distances for the database case. These variables are all quantized into corresponding universe of discourse according to the robot's mechanism specifications and the designer's experience. Therefore, the design of the quantization of the variables may be different from person to person. The turning angle and the stride of a quadruped robot in a gait cycle are limited by its mechanical constraints and the ground roughness [41]. For example, when TITAN-VIII crawls on the ground with the roughness less than 5 cm, its maximized turning angle of a standstill-turning gait and maximized stride of a straightgoing gait are $\pi/4$ rad and 22 cm, respectively [47]. Obviously, the stable stride should be less than the maximized stride in a gait cycle. The quantization of $d_{\min}$, ψ, and ϕ is shown in Table II, where x, y, and w denote the quantization values of $d_{\min}$, ψ, and ϕ, respectively.

TABLE II
QUANTIZED $d_{\min}$, ψ, AND ϕ

$d_{\min}$ [m]	ψ [rad]	ϕ [rad]	quantized level x, y, w
≤ 0.500	$\leq -\pi/4$	$-\pi/4$	-4
0.625	$-3\pi/16$	$-3\pi/16$	-3
0.750	$-\pi/8$	$-\pi/8$	-2
0.875	$-\pi/16$	$-\pi/16$	-1
1.000	0	0	0
1.125	$\pi/16$	$\pi/16$	1
1.250	$\pi/8$	$\pi/8$	2
1.375	$3\pi/16$	$3\pi/16$	3
≥ 1.500	$\geq \pi/4$	$\pi/4$	4

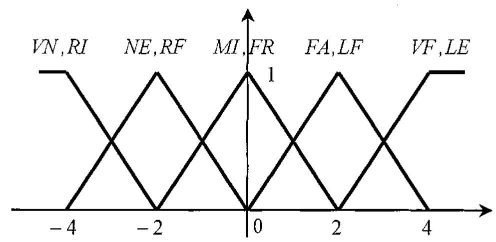

Fig. 9. Membership functions.

Having made the quantizations of the system variables, the quantized data are then converted into suitable linguistic variables which may be viewed as labels of fuzzy sets. For $d_{\min}$, the following linguistic variables are used again: *Very Near (VN), Near (NE), Middle (MI), Far (FA)*, and *Very Far (VF)*. For ψ and ϕ, the following linguistic variables are introduced: *Right (RI), Right-Front (RF), Front (FR), Left-Front (LF)*, and *Left (LE)*. A fuzzy set is defined by assigning the grade of membership values to each element of the universe of discourse. There are many types of membership functions, e.g., the bell shaped, the triangular shaped, and the trapezoidal shaped, etc. The choice of membership function mainly depends on the user's preference. For simplicity, the triangular-shaped function shown in Fig. 9 is used in this application.

2) Combined Rule Bases: Fuzzy inference is characterized by the linguistic description in the form of fuzzy implication rules. In this application, the fuzzy inference is based on

TABLE III
LINGUISTIC RULE TABLE FOR THE THIRD AND NINTH CATEGORIES OF ENVIRONMENT

	No.3	$d_{\min}$						No.9	$d_{\min}$				
	ϕ	VN	NE	MI	FA	VF		ϕ	VN	NE	MI	FA	VF
	RI	RI	RI	RI	RI	RI		RI	RI	RI	RI	RI	RI
	RF	RF	RF	RF	RF	RF		RF	RI	RI	RF	RF	RF
ψ	FR	FR	FR	FR	FR	FR	ψ	FR	RI	RI	RF	RF	FR
	LF	FR	FR	LF	LF	LF		LF	RI	RI	FR	FR	FR
	LE	FR	FR	LF	LE	LE		LE	RI	RI	FR	FR	FR

the combined rule bases. The changes of environment of the quadruped robot are observed by the environment recognizer. After selecting the corresponding rule base which is adequate for the observed environment, a feedback control is accomplished by the selected one. The recognizer observes the environment at a gait cycle to determine whether the current rule base can control the robot well and, if necessary, exchange the rule base. If the observed environment belongs to the ith category, the fuzzy-rule base for the next control duration is the ith one. For example, some typical fuzzy rules belonging to different environment categories are listed as follows:

IF category is 2 AND $d_{\min}$ is *NE* AND ψ is *RF*
THEN ϕ is *RI*
IF category is 3 AND $d_{\min}$ is *NE* AND ψ is *RF*
THEN ϕ is *RF*
IF category is 9 AND $d_{\min}$ is *NE* AND ψ is *RF*
THEN ϕ is *RI*
IF category is 16 AND $d_{\min}$ is *NE* AND ψ is *RF*
THEN ϕ is *FR*
IF category is 22 AND $d_{\min}$ is *NE* AND ψ is *RF*
THEN ϕ is *LE*.

The rule base changes with the environment category, e.g., Table III presents the rule bases for the third and ninth environment categories. All other fuzzy rule bases of this application are not listed here due to the space limitation.

The inference mechanism employed in fuzzy logic controllers is generally based on various reasoning schemes. The inference result can be obtained by using several different algorithms. Mamdani's strategy—Mamdani's fuzzy reasoning method based on MAX–MIN inference operator is used to perform fuzzy inference in this application.

3) Defuzzification: Defuzzification describes the mapping from a space of fuzzy control action into a nonfuzzy control action. The defuzzification produces a nonfuzzy action that best represents the inferred fuzzy output. Many strategies can be used for carrying out the defuzzification. The center-of-gravity method is adopted in this paper, that is

$$w = \frac{\sum_{i=1}^{n} w_i \mu_U(w_i)}{\sum_{j=1}^{n} \mu_U(w_j)} \tag{17}$$

where $n = 9$ which is the number of the elements of the discrete universe of discourse [−4, 4], w_i denotes the ith element of the universe of discourse, and $\mu_U(w_i)$ represents the membership of the fuzzy set as the output of the fuzzy inference. Based on the linguistic control rules, the decision-lookup tables constructed

TABLE IV
DECISION LOOKUP TABLE FOR THE THIRD CATEGORY OF ENVIRONMENT

		x								
	w	−4	−3	−2	−1	0	1	2	3	4
	−4	−4	−4	−4	−4	−4	−4	−4	−4	−4
	−3	−3	−3	−3	−3	−3	−3	−3	−3	−3
	−2	−2	−2	−2	−2	−2	−2	−2	−2	−2
	−1	−1	−1	−1	−1	−1	−1	−1	−1	−1
y	0	0	0	0	0	0	0	0	0	0
	1	0	0	0	1	1	1	1	1	1
	2	0	0	0	1	2	2	2	2	2
	3	0	0	0	1	2	3	3	3	3
	4	0	0	0	1	2	3	4	4	4

TABLE V
DECISION LOOKUP TABLE FOR THE NINTH CATEGORY OF ENVIRONMENT

		x								
	w	−4	−3	−2	−1	0	1	2	3	4
	−4	−4	−4	−4	−4	−4	−4	−4	−4	−4
	−3	−4	−4	−4	−3	−3	−3	−3	−3	−3
	−2	−4	−4	−4	−3	−2	−2	−2	−2	−2
	−1	−4	−4	−4	−3	−2	−2	−2	−2	−2
y	0	−4	−4	−4	−3	−2	−2	−2	−1	0
	1	−4	−4	−4	−3	−1	−1	−1	0	0
	2	−4	−4	−4	−2	0	0	0	0	0
	3	−4	−4	−4	−2	0	0	0	0	0
	4	−4	−4	−4	−2	0	0	0	0	0

using the center-of-gravity method are obtained for the corresponding environment category. For instance, Tables IV and V are the decision-lookup tables for the third and ninth environment categories, respectively.

By properly scaling, the real navigation information on the turning angle can be generated according to the content of the decision-lookup tables.

C. Navigation Control Algorithm

According to the above discussion, the navigation control algorithm is induced as follows.

Step 1) Give the positions of the starting point and the specified target and, if necessary, input the environment database including the desired environment radius.

Step 2) Evaluate the target orientation angle ψ and the distance between the robot and the specified target.

Step 3) If the target distance is less than S, then go to Step 12), otherwise continue.

Step 4) Evaluate the obstacle distances d_f, d_l, d_r, d_{lf}, and d_{rf} according to the current robot posture and the environment database; or input the linguistic description for the obstacle distances, which are then transformed into the numerical symbols.

Step 5) Compare the obstacle distances to confirm the critical obstacle distance.

Step 6) According to the obstacle distances and the environment radius, the current environment category is recognized by the environment recognizer (ART-II network).

TABLE VI
CONNECTION WEIGHTS OF THE ART-II NETWORK, WHERE i DENOTES THE INPUT CHANNEL AND j REPRESENTS THE CATEGORY

j	i = 1	2	3	4	5	6	j	i = 1	2	3	4	5	6
1	4.08	4.08	4.08	4.08	4.08	4.08	17	5.77	5.77	5.77	0.00	0.00	0.00
2	4.77	0.00	4.77	4.77	4.77	4.77	18	5.77	5.77	0.00	5.77	0.00	0.00
3	4.77	4.77	0.00	4.77	4.77	4.77	19	5.77	5.77	0.00	0.00	5.77	0.00
4	4.77	4.77	4.77	0.00	4.77	4.77	20	5.77	5.77	0.00	0.00	0.00	5.77
5	4.77	4.77	4.77	4.77	0.00	4.77	21	5.77	0.00	5.77	5.77	0.00	0.00
6	4.77	4.77	4.77	4.77	4.77	0.00	22	5.77	0.00	5.77	0.00	5.77	0.00
7	5.00	0.00	0.00	5.00	5.00	5.00	23	5.77	0.00	5.77	0.00	0.00	5.77
8	5.00	0.00	5.00	0.00	5.00	5.00	24	5.77	0.00	0.00	5.77	5.77	0.00
9	5.00	0.00	5.00	5.00	0.00	5.00	25	5.77	0.00	0.00	5.77	0.00	5.77
10	5.00	0.00	5.00	5.00	5.00	0.00	26	5.77	0.00	0.00	0.00	5.77	5.77
11	5.00	5.00	0.00	0.00	5.00	5.00	27	7.07	7.07	0.00	0.00	0.00	0.00
12	5.00	5.00	0.00	5.00	0.00	5.00	28	7.07	0.00	7.07	0.00	0.00	0.00
13	5.00	5.00	0.00	5.00	5.00	0.00	29	7.07	0.00	0.00	7.07	0.00	0.00
14	5.00	5.00	5.00	0.00	0.00	5.00	30	7.07	0.00	0.00	0.00	7.07	0.00
15	5.00	5.00	5.00	0.00	5.00	0.00	31	7.07	0.00	0.00	0.00	0.00	7.07
16	5.00	5.00	5.00	5.00	0.00	0.00	32	1.00	0.00	0.00	0.00	0.00	0.00

Step 7) Select the decision lookup table corresponding to the current environment category.

Step 8) Transform the critical obstacle distance $d_{\min}$ (for the database case) and the target orientation angle ψ into corresponding quantization values x and y, respectively.

Step 9) According to x and y, look up the selected decision table for w.

Step 10) Determine the turning angle ϕ for a standstill-turning gait, then the robot performs the standstill-turning gait, otherwise, the robot takes a straight-going gait with the stable stride S when $w = 0$.

Step 11) Go to Step 2).

Step 12) End.

IV. SIMULATION AND EXPERIMENT

As shown in Fig. 2, the main specifications of TITAN-VIII relative to the problem are: $m = 100$ mm, $n = 200$ mm, $L_0 = 252$ mm, and $H_0 = 236$ mm. If the ground roughness is less than 50 mm, TITAN-VIII can implement the maximized turning angle of $\pi/4$ in a standstill-turning gait cycle or the maximized stride of 220 mm in a straight-going gait cycle [47]. Therefore, the stable stride of a straight-going gait is given as $S = 200$ mm under the circumstances. In addition, the environment radius is defined as $R = 2$ m according to the robot specifications. Utilizing the training data provided in Section III-A, the ART-II network is trained then included into the control loop as the environment recognizer, whose connection weights between F_1 and F_2 are obtained and listed in Table VI. Consequentially, simulations and experiment can be conducted according to the navigation control algorithm as above.

A. Simulation Results

In the following simulation examples, the ground roughness was less than 50 mm, the positions of five convex obstacles and three concave obstacles were, in meters: (2.0, 2.0), (1.5, 4.0), (4.0, 4.0), (6.0, 3.0), (3.0, 6.0), (6.0, 6.0), (4.0, 1.0), and (5.0, 7.0), respectively. The starting and target positions were provided to the control system. Based on the environment database, simulations were conducted three times. The environment category was first recognized at a gait cycle, the command on turning angle was then found and provided to the robot from

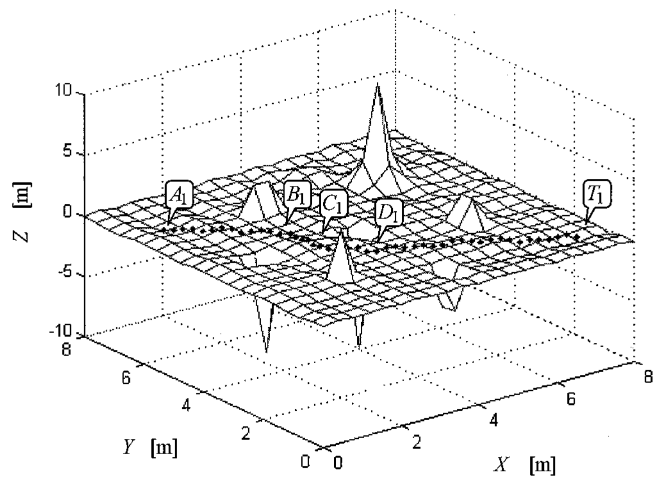

Fig. 10. Path of the quadruped robot from A_1 to T_1.

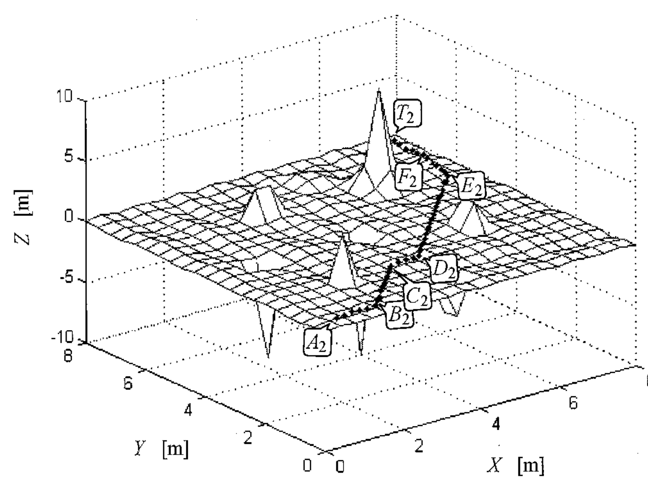

Fig. 11. Path of the quadruped robot from A_2 to T_2.

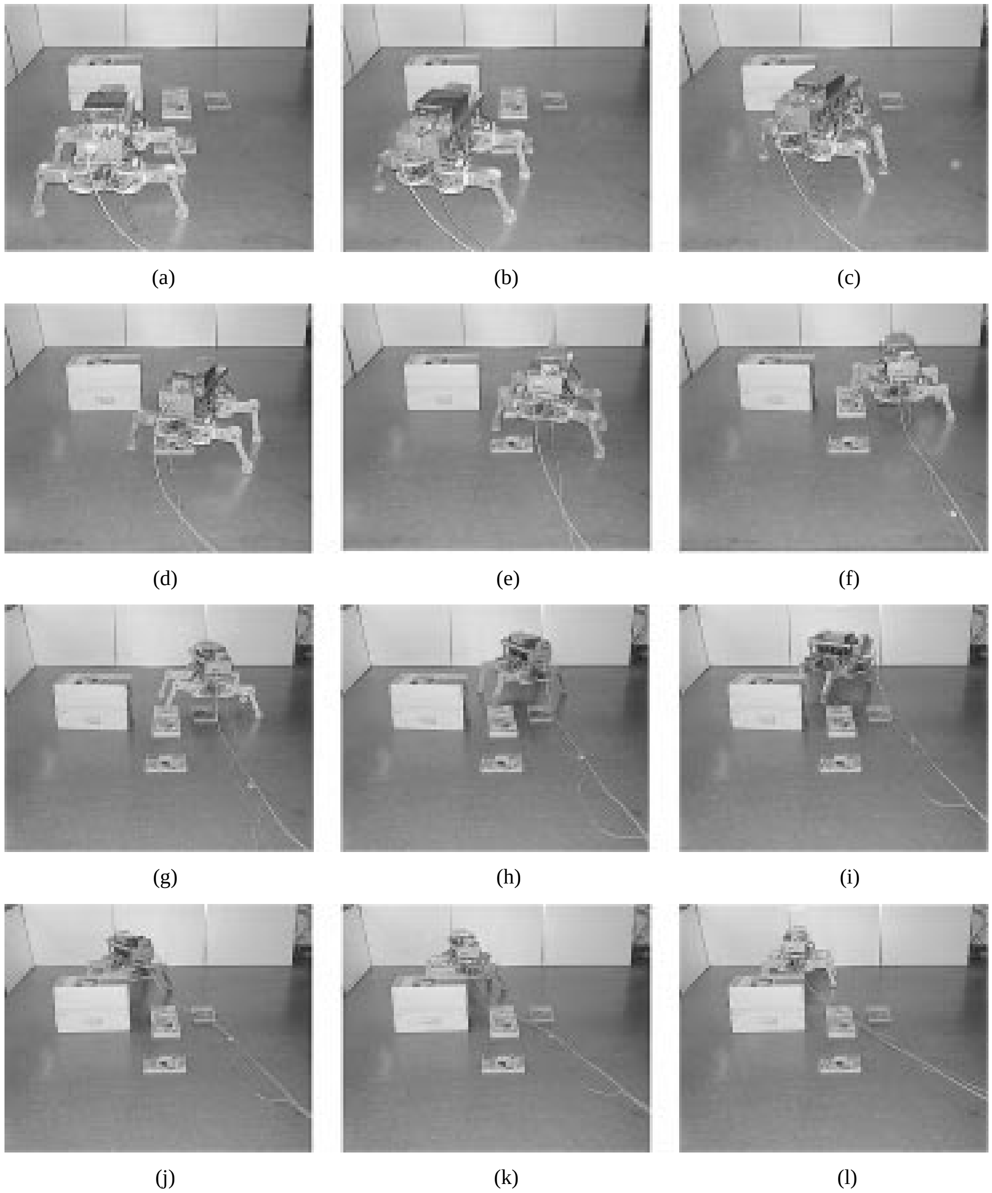

Fig. 12. Experimental result avoiding obstacles in our laboratory.

the corresponding decision lookup table. If the turning angle was zero the robot made a straight-going gait with the stable stride, otherwise the robot took a standstill-turning gait with the desired turning angle. Fig. 10 presents the walking path of the quadruped robot from the starting point A_1(0.8, 6.4: in meters) to the target T_1(7.5, 1.0: in meters), where each dot denotes a stable stride of the robot. Here, we further give the navigation result of the robot at the turning-point B_1, C_1 and D_1. The environment categories of the robot at these points were no. 8, no. 19 and no. 16, respectively. The turning angle of the robot at the points were $-\pi/4$, $\pi/4$ and $\pi/8$, respectively. Fig. 11 shows the path of the quadruped robot walking from the starting point A_2(0.5, 0.4: in meters) to the target T_2(7.5, 7.5: in meters). Similarly, the navigation results of the robot at five turning-point B_2, C_2, D_2, E_2, and F_2 were as follows: the environment categories were recognized as no. 5, no. 5, no. 13, no. 3, and no. 3, respectively, and the robot turning-angles at these points were $\pi/4$, $-\pi/4$, $\pi/4$, $3\pi/16$, and $\pi/16$, respectively.

B. Experimental Result

To further verify the effectiveness of the proposed algorithm, a laboratory experiment has also been conducted to navigate TITAN-VIII by the linguistic input. There was an obstacle the robot cannot step on/over and three convex objects with height of 30 mm the robot can step on/over on the experimental terrain. The positions of the starting point and target were also inputted to the control system. The obstacle distances were provided in the fuzzy language by human–machine interface through the keyboard in the numerical symbol. Fig. 12 shows the real experimental photograph of TITAN-VIII navigated to walk from the starting point [Fig. 12(a)] to the target [Fig. 12(l)]. The navigation results of the robot at some typical points are further given as follows: At Fig. 12(a), five obstacle distances were provided to the controller in *NE*, *VF*, *VF*, *VF*, and *VF*, respectively, then, the current environment category was recognized as no. 2, and hence, the robot obtained the navigation command of a turning angle $\phi = -\pi/4$ from the second decision lookup table.

At Fig. 12(b), five obstacle distances were *VF*, *VF*, *VF*, *NE*, and *VF*, respectively, the current environment category was then recognized as no. 5 and the turning angle of the robot was $\phi = 0$ from the fifth decision lookup table, and hence, the robot performed a straight-going gait cycle with the stable stride S. At Fig. 12(f), five obstacle distances were *VF*, *VN*, *VF*, *VF*, and *VF*, respectively, the current environment category was recognized as no. 3, and the turning angle was $\phi = 0$, therefore, the robot took a straight-going gait and stepped on a convex object. And at Fig. 12(j), five obstacle distances were provided to the controller in *VF*, *VF*, *VF*, *VF*, and *VF*, respectively, the current environment category was recognized as no. 1, and the turning angle was $\phi = -\pi/4$ from the first decision lookup table.

V. Conclusion

When an environment where a quadruped robot walks is very complex and uncertain, adaptive navigation control is necessary. This paper has considerably extended the existing locomotion control of quadruped robots by introducing the adaptive navigation into gait generation and implementation. The adaptive navigation has been realized through online recognition of environment category, selection of an adequate rule base to the recognized environment, and fuzzy inference based on the selected fuzzy-rule base. Outperforming the existing applications of ART basic principle, we have successfully used an ART-II network to recognize the environment category after its offline learning. Furthermore, this recognizer can be applied to other locomotion machines including mobile robots and other legged robots.

Based on the online recognition of environment categories, a fuzzy controller has been designed and implemented by the adaptive selection of fuzzy-rule base in response to changes of environment category. The robustness of the controller is guaranteed so long as each rule base is established properly to the corresponding environment category. Therefore, the proposed fuzzy control scheme is superior to classical/conventional ones in robust stability and real-time operation due to the implementation of a lookup table. The feasibility and effectiveness of the proposed controller has been demonstrated through the simulation and experiment. It should be pointed out that, if a human operator can be replaced by a sophisticated vision system to identify various obstacles and to measure the obstacle distances, the full autonomous walking of a quadruped robot will be entirely realized by means of the proposed control algorithm.

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