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FUZZY REACTIVE CONTROL OF WHEELED MOBILE ROBOT

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This paper proposes a sensor based navigation method with a fuzzy combiner for navigation of a mobile robot in uncertain environments. We discuss a fuzzy approach to path design and control of simple individual behaviours of a wheeled mobile robot in an unknown 2D environment with static obstacles. A strategy of reactive navigation is developed including three main behaviours: reaching the middle of a collision-free space behaviour, goal-seeking behaviour and wall-following behaviour. These simple individual behaviours are achieved by means of fuzzy inference systems. It is assumed that each low-level behaviour has been well developed at the design stage and then fused by the fuzzy combiner of behaviours to determine proper actions acting on the environment at the running stage. The fuzzy combiner can fuse low-level behaviours so that the mobile robot can go for the goal position without colliding with obstacles. The fuzzy combiner is a soft switch that chooses more than one low-level action to be active with different degrees through fuzzy combination at each time step. The output of the navigation level is fed into a fuzzy tracking controller that takes into account the dynamics of the mobile robot. A computer simulation have been conducted to illustrate the performance of the proposed fuzzy combiner of behaviours by a series of experiments on an emulator of the wheeled mobile robot Pioneer-2DX.

Key words: behaviour control, fuzzy logic, wheeled mobile robots

1. Introduction

The development of techniques for autonomous navigation constitutes one of the major trends in the current research on robotics. Many researchers have pointed out the interest of fuzzy logic for mobile robot control. In general, fuzzy logic has been used to consider uncertainties due to limitations in a perception system, unstructured environment, and disturbances in robot dynamics. The most classical type of behaviour used in mobile robots is the trajectory tracking. The trajectory tracking control implies an a priori trajectory design to be given for the entire robot operation. The kinematics and dynamics of mobile robots is complex and non-linear, and is hard to model in general. These characteristics led the authors of this paper to use different control approaches: robust control, adaptive control, neural networks and fuzzy control for the trajectory tracking. All of them have been tested on the real mobile robot Pioneer 2Dx with good results (Giergiel *et al.*, 2000, 2002; Hendzel and Żylski, 1997).

Expansion of the range of robot tasks and robot autonomy created a need to generate trajectories on-line. For example, robots need to adjust trajectories on-line to avoid collisions with obstacles in the workspace while approaching a given goal point. There are a lot of studies on the trajectory generation for robots using various approaches e.g. Arkin (1998), Berenstain and Koren (1989), Verbruggen *et al.* (1999), Zalzala and Morris (1996). The artificial potential field method is a popular tool for on-line trajectory generation with inherent collision avoidance (Arkin, 1998; Berenstain and Koren, 1989; Żylski, 2002). A comprehensive overview of the reactive navigation, robot behaviour and behaviour-based control field can be found in the books by Arkin (1998), Driankov and Saffiotti (2001), Verbruggen *et al.* (1999). Several neural network models, e.g. Berenstain and Koren (1989), Giergiel *et al.* (2000), Hendzel and Żylski (1997), Hendzel (2003), Zalzala and Morris (1996), were proposed to generate real-time trajectories. Although many solutions have already been reported in the literature, the continuing development of new proposals suggests that this field has not settled down yet. Several researchers have already argued the importance of looking at a mobile robot as a set of elementary behaviours (Arkin, 1998; Driankov and Saffiotti, 2001; Hendzel, 2003; Latombe, 1991). Elementary behaviours are important components of reactive control in which the mobile robot must continuously interact with its environment. Reactive control means that all decisions are based on currently perceived sensory information (Berenstain and Koren, 1989; Benreguieg *et al.*, 1998; Giergiel *et al.*, 2000; Hendzel, 2003).

In this paper, a fuzzy inference system approach is proposed for the collision-free trajectory generation in an unknown environment. A strategy of reactive navigation is developed including three main behaviours: reaching the middle of a collision-free space behaviour, goal-seeking behaviour and wall-following behaviour. The fundamental idea of the behavioural control is to view mobile robot missions as a simultaneous and temporal execution of a set of elementary behaviours. Numerous behaviour co-ordination mechanisms have been proposed. For a detailed overview, discussion and comparison of behaviour co-ordination mechanisms see the following papers by Driankov and Saffiotti (2001), Lin and Chung (1999), Zalzala and Morris (1996). The behaviour co-ordination mechanisms can be divided into two main classes: arbitration and command fusion (Driankov and Saffiotti, 2001). The command fusion mechanisms provide for a co-ordination scheme that allows all behaviours to simultaneously contribute to the control of the system in a co-operative manner.

The command fusion approach with a fuzzy mechanism, which allows for weighted combination of behaviours (Driankov and Saffiotti, 2001; Lin and Chung, 1999), is used in this work to solve the task of reactive navigation of a mobile robot in uncertain environments. The proposed navigator consists of two main behaviours: reaching the middle of a collision-free space behaviour and goal-seeking behaviour. It is assumed that each low-level behaviour has been well set forth at the design stage and then fused by the fuzzy combiner of behaviours to determine proper actions acting on the environment at the running stage. The fuzzy combiner can fuse low-level behaviours so that the mobile robot can go for the goal position without colliding with obstacles. The output of the navigation level is fed into a fuzzy tracking controller that takes into account the dynamics of the mobile robot. The structure of the fuzzy controller for a nonholonomic mobile robot is derived using the filtered error approach (Giergiel *et al.*, 2002). This work is an extension of former work (Hendzel, 2004).

2. Fuzzy logic for behaviour design

The mechanical structure of the mobile robot, like Pioneer-2DX, is shown in Fig. 1.

The presented robot has two degrees of freedom. Its posture is defined as $[x_A, y_A, \beta]^\top$, where (x_A, y_A) is the position of the point A, and β is the heading angle of the robot with respect to the absolute coordinates (x, y). The kinematics of the mobile robot is defined by

$$\begin{bmatrix} \dot{x}_A \\ \dot{y}_A \\ \dot{\beta} \end{bmatrix} = \begin{bmatrix} V_{Am}\cos\beta & 0 \\ V_{Am}\sin\beta & 0 \\ 0 & \omega_m \end{bmatrix} \begin{bmatrix} u_v \\ u_\beta \end{bmatrix} \tag{2.1}$$

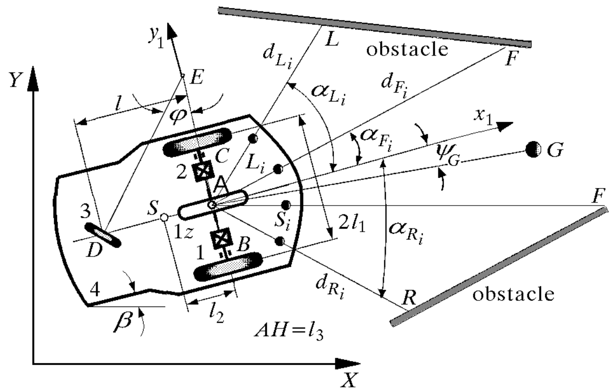


Fig. 1. Mobile robot

where the maximum linear speed is denoted by V_{Am}, the angular one by ω_m, u_v is the multiplying coefficient of the maximum linear velocity of the point A and u_β is the multiplying coefficient of the maximum angular velocity of the frame.

2.1. An overview of the navigator

The described mobile robot is equipped with eight ultrasonic sensor rings as depicted in Fig. 1. The position of the sensor s_i is L_i. The sensors are divided into three groups. One group is composed of three, two and three neighbouring sensors. This gives a distance to the obstacle d_{Li}, d_{Fi}, d_{Ri} in its field of view, respectively, where $d_{min} \leqslant d_{(\cdot)} \leqslant d_{max}$. Each sensor covers an angular view which is oriented by angles α_{Li}, α_{Fi}, α_{Ri}, respectively.

To solve the trajectory tracking problem for a non-holonomic mobile robot with regard to the vehicle dynamics (Giergiel *et al.*, 2000, 2002, Hendzel and Żylski, 1997; Hendzel, 2003), it is assumed that the current configuration of the mobile robot $\boldsymbol{x}_d = [x_A, y_A, \beta]^\top$ (desired kinematics) is generated at each time step by the fuzzy navigator which generates the vector of multiplying coefficients $\boldsymbol{u}_B = [u_v, u_\beta]^\top$ based on the environment information $d_{(\cdot)}$. In this work, three navigation tasks are discussed: reaching the middle of a collision-free space behaviour, goal-seeking behaviour and wall-following behaviour. A diagram of the navigator and controller architecture is shown in Fig. 2.

2.2. Reaching the middle of a collision-free space behaviour

Let the input variables of the fuzzy navigator are respectively the normalized distances measured on the right $d_R^n = d_R/(d_R + d_L)$, on the left

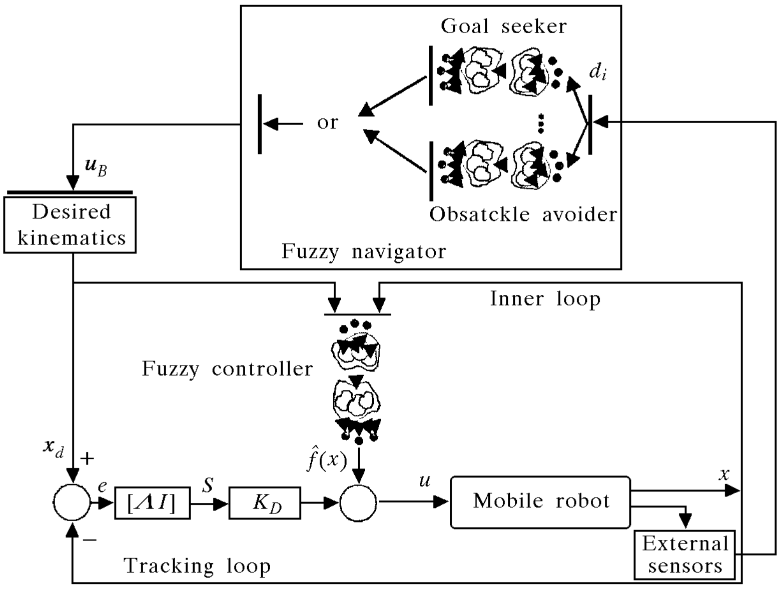


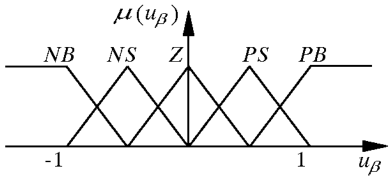
Fig. 2. Navigator and controller

(a)

d_R^n \ d_L^n	Z	S	M	B	VB
Z	Z	PS	PS	PB	PB
S	NS	Z	PS	PS	PB
M	NS	NS	Z	PS	PS
B	NB	NS	NS	Z	PS
VB	NB	NB	NS	NS	Z

(b)

u_β \ d_F^n	Z	S	M	B	VB
NB	Z	Z	S	S	S
NS	Z	S	M	B	B
Z	Z	S	M	B	VB
PS	Z	S	M	B	B
PB	Z	Z	S	S	S



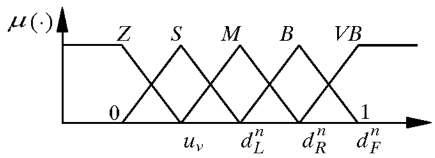


Fig. 3. Angular (a) and linear (b) velocity coefficient rules, respectivly

$d_L^n = d_L/(d_R + d_L)$ and in front of the robot $d_F^n = d_F/\eta$. In the above the following denote: $d_L = \min(s_2, s_3)$, $d_F = \min(s_4, s_5)$, $d_R = \min(s_6, s_7)$ and η is the distance beyond which the obstacle is not taken into account. The used navigator is build with fuzzy inference systems based on a set of rules such as: if d_R^n is A_i and d_L^n is B_i then u_β is C_i, and if d_F^n is D_i then u_v is E_i, where A_i, B_i, C_i, D_i, E_i are linguistic labels of the inputs d_R^n, d_L^n, d_F^n and the outputs u_β, u_v. The shape of the membership functions is triangular and the universes of discourse are normalized between -1 and 1 for u_β and between 0 and 1 for u_v. The whole rule-base is presented in Fig. 3 in two decision tables (Benreguieg *et al.*, 1998).

The Max-Prod inference algorithm is used to evaluate the rules, and the center average method is used for the defuzzyfication. To illustrate the performance of the proposed algorithms for path planning and control, a simulator of the mobile robot and its workspace was built in the Matlab/Simulink environment (Hendzel, 2003). An example of the resulting navigation "reaching the middle of a collision-free space" behaviour and control is shown in Fig. 4a,b. The impacts of the sensors is depicted in Fig. 4c.

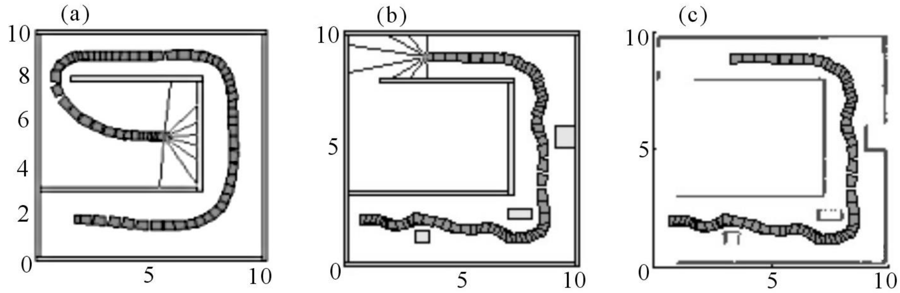


Fig. 4. Reaching the middle of a collision-free space behaviour

2.3. Goal seeking behaviour

The task of goal seeking behaviour consists in on leading the mobile robot to the desired point G as shown in Fig. 1. It means minimalization of the distance $\|A, G\|$ and the angle ψ_G which is the angular deviation needed to reach the goal. In this task, the navigator is built with a fuzzy inference system. The whole control rule-base, deducted from a human intuitive experience, is represented by twelve rules and fuzzy sets shown in two decision tables in Fig. 5.

Figure 6a presents a numerical example of the navigation. The action u_β, u_v generated by the fuzzy navigator for the point $G(9,9)$ is shown Fig. 6b. The driving torques M_1 and M_2 generated by the adaptive fuzzy controller are presented in Fig. 6c.

2.4. Wall-following behaviour

In environments without concave obstacles the combination of analysed behaviours is sufficient for the navigation. In the case of concave obstacles it

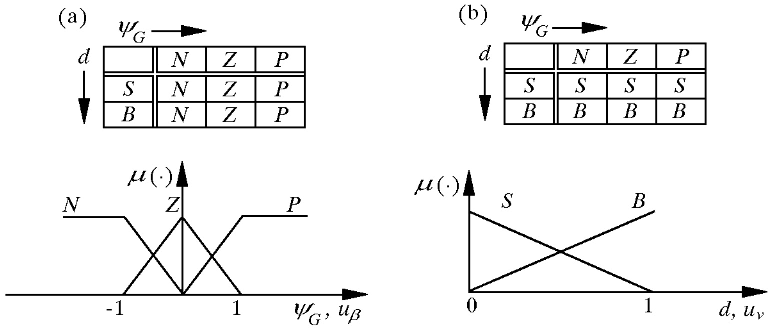


Fig. 5. Angular (a) and linear (b) velocity coefficient rules

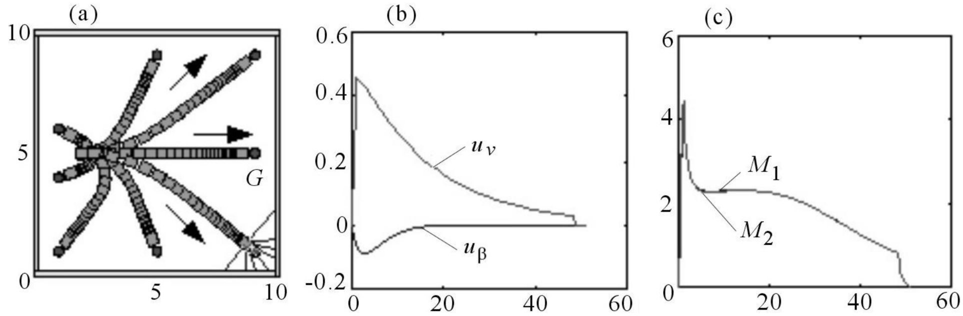


Fig. 6. Goal seeking behaviour

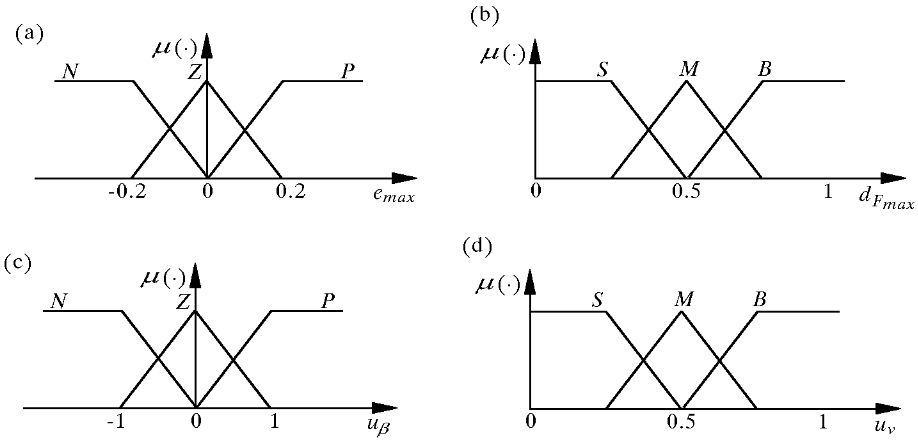


Fig. 7. Membership functions

is necessary to analyse the strategy of wall-following. The input variables of the fuzzy inference system are error defined ones $e = \min(d_R, d_F) - d_0$, where d_0 is a desired distance to the wall (e.g. follow the right wall) and d_F gives the distance to the wall. The navigator is the built with the fuzzy inference system based on a set of rules such as: if e is A_i then u_β is C_i, and if d_F is D_i then u_v is E_i, where A_i, C_i, D_i, E_i are linguistic labels of the input signals and the outputs u_β, u_v. The shape of the membership functions is triangular. The fuzzy sets are depicted in Fig. 7.

An example of the resulting navigation with the impacts of the sensors is shown in Fig. 8 (follow left wall) and Fig. 10b (follow right wall).

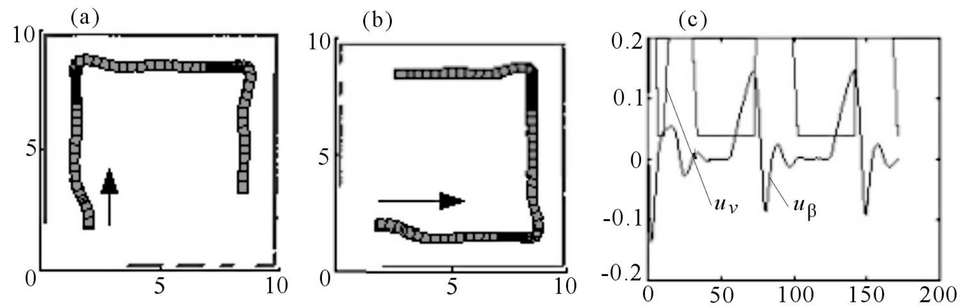


Fig. 8. Wall-following behaviour

The action u_β, u_v generated by the fuzzy navigator is presented in Fig. 8c.

3. Fuzzy combiner

This section introduces structures and functions of the proposed fuzzy navigator and its key component, i.e. fuzzy combiner of two behaviours: obstacle avoidance and goal seeking. It is assumed that each low-level behaviour has been well formulated at the design stage and then fused by the fuzzy combiner of behaviours to determine proper actions in the environment at the running stage, as shown in Fig. 9.

When the mobile robot encounters an obstacle which obstructs the goal, these two behaviours are in conflict. In this paper, we adopt the concept of gating architecture (Driankov and Saffiotti, 2001; Lin and Chung, 1999; Zalzala and Morris, 1996), shown in Fig. 10, to solve this conflict.

In the proposed multiobjective fuzzy navigator, we use the fuzzy combiner (FC) to combine low-level modules which are denoted as the obstacle avoider

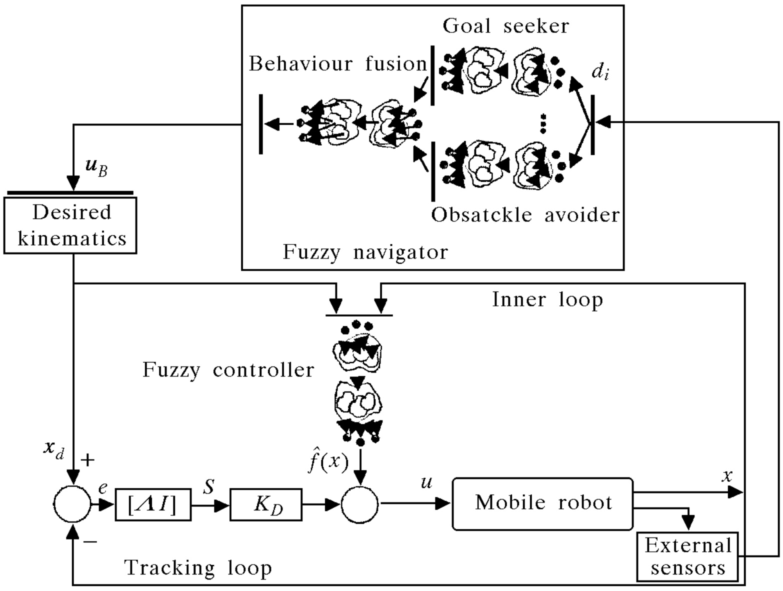


Fig. 9. Architecture of the navigator and controller

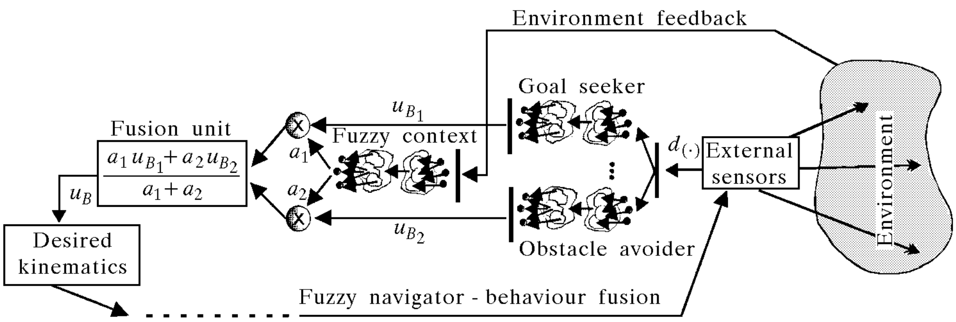


Fig. 10. Basic structure of the fuzzy navigator

(OA) and goal seeker (GS), see Fig. 10. Each module receives distances sensed by the ultrasonic sensors $d_{(\cdot)}$ and produces output signals. The OA determines the action $\boldsymbol{u}_{B_2} = [u_{vOA}, u_{\beta OA}]^\top$ for the behaviour of obstacle avoidance, while the GS determines the action, $\boldsymbol{u}_{B_1} = [u_{vGS}, u_{\beta GS}]^\top$ for the behaviour of goal seeking. These two behavioural modules work independently and their actions are fused by the FC to produce the action $\boldsymbol{u}_B = [u_v, u_\beta]^\top$ for the navigation. It is assumed that each low-level module has been well designed to serve a particular objective of the required multiple objectives. Many techniques have been development to design a single objective. These techniques include fuzzy modelling, neural network, etc. As can be seen in Fig. 10, the proposed FC is composed of two elements, a fuzzy context unit and an integration unit. The fuzzy context selects a set of weights a_i for the two low-level module actions according to the two control status signals J_i (the "context") generated by the environment feedback signal at each time step.

The control status signals indicate the status of the control objectives and are defined by

$$J_i = \text{ degree(distance of goal}_i) \qquad i = 1,2 \tag{3.1}$$

where any distance measure can be used. The control status signal J_i indicates the degree that the ith control objective is achieved at the current time step. Such information can be obtained by simply checking the status of each control objective independently. The weights a_i produced by the fuzzy context determine the degree of the low-level control action $\boldsymbol{u}_{B_i}$. With these weighting values, the integration unit will carry out linearly weighted summation to combine the two low-level actions into the final action $\boldsymbol{u}_B$ as the output of the FC. Due to the powerful capaabilities of the fuzzy modelling, we employ the fuzzy techniques to realise the FC in this paper.

4. Design fuzzy combiner

In this section, the proposed FC is applied to two behaviours: obstacle avoidance and goal seeking – to show its performance and applicability. To design the proposed FC, first we need to define two control status signals J_1 and J_2. Let the input variables of the fuzzy navigator are the measured distances on the right $d_R = \max(s_6, s_7, s_8)$, on the left $d_L = \max(s_1, s_2, s_3)$, and at the front $d_F = \min(s_4, s_5)$, where d is the distance between the point A and G. Let us define the errors: $e_R = d_R - d$, $e_L = d_L - d$, $e_F = d_F - d$, and ψ_G – the angular deviation needed to reach the goal G. Control status signals are defined according to the two control objectives

$$J_1 = [e_L, e_R, e_F]^\top \qquad J_2 = \psi_G \tag{4.1}$$

They are normalised to be held within $e_{min} \leqslant e_{(\cdot)} \leqslant e_{max}$ and $-\pi \leqslant \psi_G \leqslant \pi$, respectively.

The used FC is built with fuzzy inference systems based on a set of rules such as: if $e_{(\cdot)}$ is A_i and ψ_G is B_i then a_1 is C_i, and if $e_{(\cdot)}$ is A_i and ψ_G is B_i

then a_2 is $\neg C_i$, where A_i, B_i, C_i are linguistic labels of the inputs $e_{(\cdot)}$, ψ_G and of the outputs a_1, a_2. The shape of the membership functions is triangular. The whole rule-base is shown in Fig. 11 in six decision tables. The set of terms for J_1 and J_2 is N-negative, P-positive and N-negative, Z-zero, P-positive, respectively, and the set of terms for a_1 and a_2 is S-small, L-large.

(a)

e_L \ ψ_G	N	Z	P
N	S	S	S
P	L	S	S

e_R \ ψ_G	N	Z	P
N	S	S	S
P	S	S	L

e_F \ ψ_G	N	Z	P
N	S	S	S
P	S	L	S

(b)

e_L \ ψ_G	N	Z	P
N	L	L	L
P	S	L	L

e_R \ ψ_G	N	Z	P
N	L	L	L
P	L	L	S

e_F \ ψ_G	N	Z	P
N	L	L	L
P	L	S	L

Fig. 11. Rule table for a_1 (a) and for a_2 (b)

In the FC, the inputs are the control status signals J_1 and J_2, and the output are the weighting values of low-level modules 1 and 2, a_1, a_2. From the rule tables we observe that module 1 will be activated, i.e. $a_1 = L$, when ($J_{11} > 0$ and $J_2 < 0$) or ($J_{12} > 0$ and $J_2 > 0$) or ($J_{13} > 0$ and $J_2 = 0$). At the same time module 2 is suppressed, i.e. $a_2 = S$. We also observe that module 2 is activated, i.e. $a_2 = L$ only when the first goal is suppressed, i.e. $a_1 = S$. The design method for the FC is straightforward. It depends heavily on expert's knowledge and precise analysis of the discussions problem.

5. Simulation

To illustrate the performance of the proposed fuzzy combiner for path planning and control, a simulator of the mobile robot and its workspace was built in the Matlab/Simulink environment first (Hendzel and Żylski, 1997). We carried out simulations in which the rule-base tables, shown in Fig. 11, were put into the Max-Min inference algorithm to evaluate the rules, and the centre average method was used for the defuzzyfication. The shape of the membership functions is triangular, see Fig. 12.

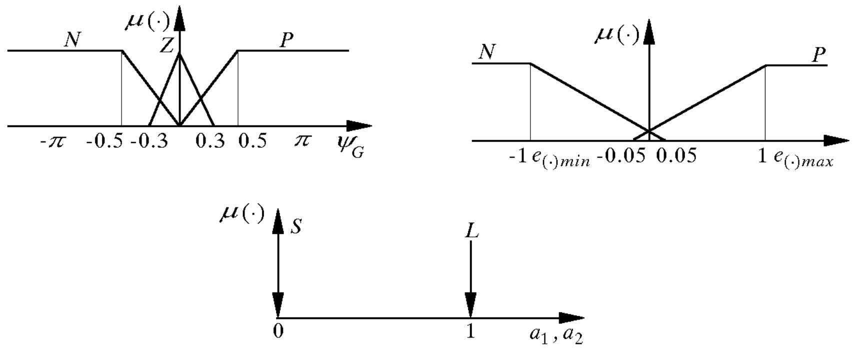


Fig. 12. Membership functions of corresponding to the fuzzy terms presented in Fig. 13

An example of the resulting fuzzy combiner is shown in Fig. 13. The mobile robot received a mission to reach the given goal position G_i from the given start position with reaching the middle of the collision-free space. The environment was considered as fixed and completely unknown.

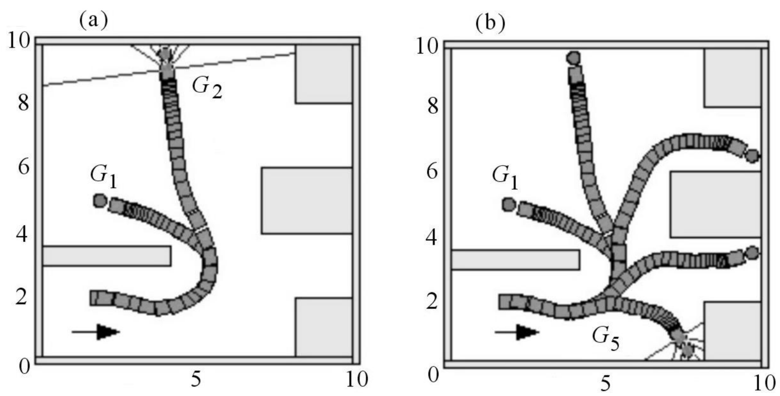


Fig. 13. Trajectories of the point A of the mobile robot in the assumed environment

The successive activation of different behaviours can be observed in Fig. 13. As shown in Fig. 14, for the given goal positions G_2 and G_5, more than one behaviour is active at the same time, which allows for soft transition.

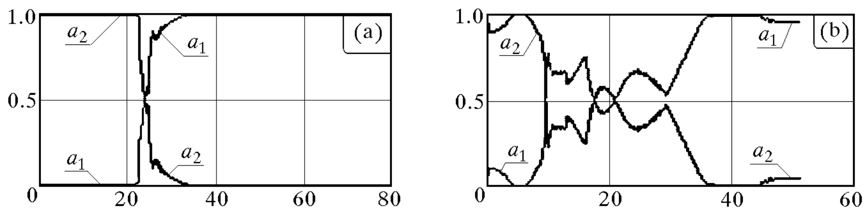


Fig. 14. Functions that modulate the weights a_1, a_2

6. Conclusion

A fuzzy navigator, based on expert's knowledge, well operating in complex and unknown environments is presented in the paper. The principle of the navigator is built on the fusion of obstacle avoidance and goal seeking behaviours. The output of the navigation level is fed into a fuzzy tracking controller that takes into account the dynamics of the mobile robot. The numerical experimental results obtained from an emulator of the mobile robot Pioneer-2DX also confirmed the effectiveness of the proposed path planning and control strategy. Future research will concentrate on applying the proposed solution as a priori knowledge used in the reinforcement learning approach.

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Rozmyte sterowanie odruchowe mobilnego robota kołowego

Streszczenie

W pracy analizuje się zagadnienie nawigacji odruchowej mobilnego robota kołowego w nieznanym otoczeniu. Przedstawiono rozmyte podejście do projektowania trajektorii ruchu i sterowania prostych indywidualnych zachowań mobilnego robota kołowego w nieznanym środowisku dwuwymiarowym ze statycznymi przeszkodami. Strategię odruchowej nawigacji zastosowano de realizacji trzech elementarnych zachowań: osiągnij środek wolnej przestrzeni, idź do celu, podążaj przy ścianie. Powyższe elementarne zachowania zrealizowano stosując układy z logiką rozmytą. Zakłada się że każde z elementarnych zachowań realizowane przez niższy poziom sterowania jest poprawnie zaprojektowane, a ich koordynacja odbywa się na wyższym poziomie hierarchii sterowania przez rozmyty układ koordynacyjny, którego zadaniem jest wygenerowanie właściwych sterowań umożliwiających realizację zadania nawigacji. Rozmyty układ koordynacji elementarnych zachowań łączy te zachowania generując zadaną trajektorię ruchu wybranego punktu mobilnego robota kołowego. Trajektoria ta jest

realizowana przez układ niskiego poziomu sterowania ruchem nadążnym mobilnego robota kołowego uwzględniającym dynamikę obiektu sterowania. W celu weryfikacji zaproponowanego rozwiązania przeprowadzono symulacje komputerowe na emulatorze mobilnego robota Pioneer-2DX.

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