New Trends in Mathematical Sciences

Navigation in multi-robot systems based on the behavioural fuzzy controller

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Abstract: Controlling a highly dynamic multi-robot system (DMRS) is a challenge scientific and technological in constant expansion. Our goal in this article is to control the DMRS and used the local interactions between the robot and its environment to produce a form of advanced intelligence in the selection of behaviours. For this, we have developed a reactive controller based on fuzzy behaviours using the concept of fuzzy logic. This controller allows mobile robots to move in an unknown environment and, at the same time, to resolve the navigation conflicts. The simulation results obtained on the pioneer P3-DX robot clearly show the effectiveness of the proposed fuzzy controller.

Keywords: Multi-robot systems, fuzzy logic, mobile robots, behavioural control architecture.

1 Introduction

Controlling a dynamic multi-robot system (DMRS) inevitably involves controlling the actions generated by each robot [1]. In the literature of collective robotics, several approaches have been proposed to control SMRS, such as centralized [2]. and distributed approaches [3]. This article focuses on navigation in DMRS using a distributed control approach. In this context, the navigation methods allow the robot to move from a start point to target point while avoiding obstacles. These methods must therefore take into account the following problems: Fixed Obstacle Avoidance Problem (FOAP); Mobile Obstacle Avoidance Problem (MOAP); and Robots Collision Avoidance Problem (RCAP).

In the FOA Problem, the environment is considered static and contains a single robot [4]. In the MOA Problem, the environment contains dynamic obstacles and several robots [5,7]. Finally, in the RCA Problem, robots could communicate with each other to find an arrangement to avoid collisions between them [8].

In this paper, the FOAP and MOAP will be considered. The main goal of this study is the design of a control architecture based on fuzzy behavioural rules, which exhibit both individual characteristics adapted to dynamic multi-robot systems and collective characteristics that promote a common goal [6]. More specifically, we propose a new process for the selection of navigation behaviours to solve the FOAP and MOAP. The proposed method allows the coordination of elementary primitives (called behaviours) in a flexible way. At the scale of the group of robots, the method also allows to achieve coordination between the robots and promoting the target tracking to solve MOAP.

The remainder of this paper is organized as follows. In the next section, the kinematic model of the robot is presented. The fuzzy controller architecture proposed for navigation will be detailed in the section III. The results of the simulation on the Pioneer 3P-DX robot will be presented in section IV. Finally, the Section V concludes the paper.

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2 Kinematic model of the robot

Identical robots are considered such that each of them has a set of sensors and effectors (actuators) allowing it to move. The proposed controller architecture will be tested on the pioneer P3-DX robots. The P3-DX robot has a circular platform and is equipped with a locomotion device consisting of two independent driving wheels, one caster-wheel, and 16 sonar sensors to cover a field perception of 360°. This platform is fairly standard and offers multiple application domains; also it is easy to control.
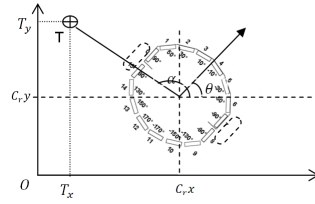

Fig. 1: Relative robot and target positions

According to the chosen platform, the robots are considered as points in the configuration space with the absolute origin O in the environment. Each robot r is located by its centre point denoted by C_r. The different configurations of the robot in the environment E at any time are determined by the following kinematic equations:

$$\begin{cases} C_r x(t) = C_r x(t-1) + |V_r(t)| cos\theta(t) \\ C_r y(t) = C_r y(t-1) + |V_r(t)| sin\theta(t) \end{cases} \tag{1}$$

with

$$\begin{cases} \theta(t) = \theta(t-1) + \Delta\theta(t) \\ |V_r(t)| = |V_r(t-1)| + \Delta|V_r(t)| \end{cases} \tag{2}$$

$$\gamma(t) = \alpha(t) - \theta(t) \tag{3}$$

$$\alpha(t) = arctan\left(\frac{T_y - C_r y}{T_x - C_r x}\right) \tag{4}$$

$\alpha(t)$ is the angle of the target, $\theta(t)$ is the robot heading angle in the configuration space and $|V_r(t)|$ is the translation velocity of robot r at time t. The relative angle that the robot makes with the target T denoted by $\gamma(t)$ is presented in figure Fig 1.

3 Fuzzy controller

To correctly implement the behaviours, a series of fuzzy decision rules are used with non-conflicting checking in their realizations, because it is possible that two opposing behaviours can be triggered at the same time. For example, turn right to target tracking and turn left to avoid the obstacle [9]. To solve this problem, we introduce the notion of context. This latter allows the determination of the behaviour should be followed by the robot based on a given environmental situation. All behaviours are not applicable in the same way. For example, the behaviour target tracking will be more appropriate when the path is free. We propose describing the context through terms in fuzzy logic [13]. Specifically, we formulate the knowledge of robots about its environment as fuzzy variables with linguistic membership functions.

The variables $\gamma(t)$ and sonar sensor data can be used as inputs variables of the fuzzy controller to effectively estimate the value of the desired heading angle $\theta(t)$ of the robot and the desired translation velocity $|V_r(t)|$. The value output variable $\theta(t)$ allows to robot the navigation in the environment with avoiding obstacles and at the same time the access to the target. The value of $\theta(t)$ and $|V_r(t)|$ is obtained by means of the Fuzzy Inference System (FIS) where we define two contexts: the first is Target Tracking and the second is Obstacle Avoidance.
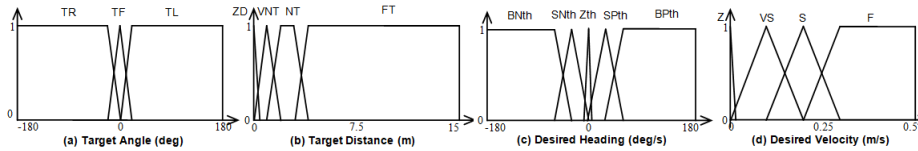

Fig. 2: Input/Output Membership Functions

Table 1: List of fuzzy rules used for implementation of target tracking behaviour.

T_D	Target Angle T_A			T_D	Target Angle T_A		
	TL	TF	TR		TL	TF	TR
Z	D_θ is $Z\theta$	D_θ is $Z\theta$	D_θ is $Z\theta$	NT	D_θ is $BP\theta$	D_θ is $Z\theta$	D_θ is $BN\theta$
	D_V is Z	D_V is Z	D_V is Z		D_V is S	D_V is S	D_V is S
VNT	D_θ is $SP\theta$	D_θ is $Z\theta$	D_θ is $SN\theta$	FT	D_θ is $BP\theta$	D_θ is $Z\theta$	D_θ is $BN\theta$
	D_V is VS	D_V is VS	D_V is VS		D_F is S	D_V is F	D_V is F

3.1 Target tracking behaviour

The first step, called fuzzification, consists to transform the real values of the input variables into fuzzy variables. For this, the controller uses the following universe of discourse: T_A Target Angle: { TL: 'Target on the Left', TF: 'Target on front', TR: 'Target on the right'}, and T_D Target Distance: { ZD:' Zero Distance', VNT: ' Very Near Target' , 'NT: ' Near Target', FT: ' Far Target' }.

The two output variables are the desired heading angle and the desired translation velocity : D_θ Desired θ : { $Z\theta$: ' Zero θ ', $BN\theta$: ' Big Negative θ ', $SN\theta$: ' Small Negative θ ', $BP\theta$: ' Big Positive θ ', $SP\theta$: ' Small Positive θ '}, abd D_V Desired velocity :$\{Z :' Zero', VS :' VerySlow', S :' Slow', F :' Fast'\}$.

The membership functions of the input variables are shown in figures Fig 2-(a); Fig 2-(b) and output variables are shown in figures Fig 2-(c); Fig 2-(d). The proposed model uses fuzzy inference system proposed in [11]. The linguistic variable value of the desired θ and the velocity is determinate using 24 fuzzy rules proposed in table 1.

3.2 Obstacle avoidance behaviour

Obstacle avoidance behaviour is triggered when one of the sensors detects an obstacle. The six sensors used by the robots have a range of 5 meters. The values transmitted by these sensors are normalized in the interval [0..1]. The fuzzy input variables and their membership functions for each sensor are shown in figure Fig 3. The outputs value of the desired θ and the velocity is determinate using 18 fuzzy rules proposed in table 2.
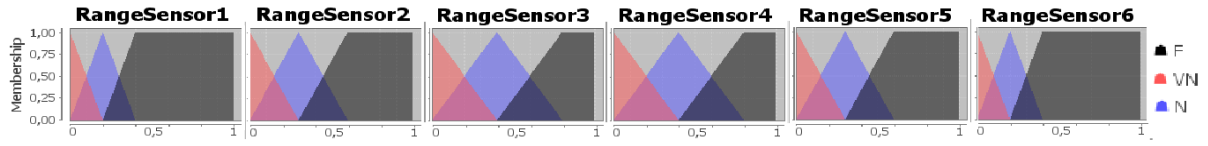
Fig. 3: Membership function of Sonar Range

Table 2: List of fuzzy rules used for implementation of obstacle avoidance behaviour.

Sensor Range	Input Fuzzy Value	Output D_θ	D_V	Sensor Range	Input Fuzzy Value	Output D_θ	D_V
Sensor 1	VN	$BN\theta$	VS	Sensor 4	VN	$BP\theta$	Z
	N	$SN\theta$	VS		N	$SP\theta$	VS
	F	$Z\theta$	S		F	$SP\theta$	F
Sensor 2	VN	$BN\theta$	VS	Sensor 5	VN	$BP\theta$	VS
	N	$N\theta$	S		N	$P\theta$	S
	F	$SN\theta$	S		F	$SP\theta$	S
Sensor3	VN	$BN\theta$	Z	Sensor 6	VN	$BP\theta$	VS
	N	$SN\theta$	VS		N	$SP\theta$	VS
	F	$SN\theta$	F		F	$Z\theta$	S

3.3 Defuzzification of output variables

When all the rules are put, we define the method of defuzzification. This step makes it possible to transform the linguistic variable values used by the fuzzy controller from fuzzy domain to the domain of the real values. The choice of the defuzzification method is usually conditioned by a compromise between the ease of implementation and performance of calculating. In this paper, we used the centre of gravity method [9] which can be determined using the following general relationship:

$$\theta^{*COG} = \frac{\int \theta \psi(\theta) d_\theta}{\int \psi(\theta) d_\theta}, v^{*COG} = \frac{\int v \psi(v) d_v}{\int \psi(v) d_v} \tag{5}$$

were θ^{*COG} is the real value of desired angle and v^{*COG} is the desired velocity obtained by the Centre of Gravity method.

3.4 Behaviors combination

To activate the appropriate FIS, the behaviour combination process uses a function $Context(R)$ which returns 1 if an obstacle is detected, otherwise it returns 0; such that $R = \{r_1, r_2, .., r_6\}$ represent the values returned by the sensors s_1 respectively $(s_2, .., s_6)$.

$$Context(R) = \begin{cases} 1 \text{ if } (\min_{\forall r_i \in R} r_i) < RangeMax \\ 0 \text{ if } (\min_{\forall r_i \in R} r_i) = RangeMax \end{cases} \tag{6}$$

This function is implemented such that RangeMax is the maximum range value of sensors fixed at 5 meters. The combination of behaviour is determined by the fuzzy controller according to the following Behavior Selection Algorithm.

4 Simulation result

In order to experimentally demonstrate the role of navigation controller, we have used a realistic simulation environment. Experimentation were performed using MobileSim Simulation Environment [12]. The experiments were conducted by

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Algorithm 1: Behavior Selection

Input: R-Set of sensor values ; C_t-Target Point ; C_r-Centre point of robot ;

$TargetDistance = \sqrt{(C_t x - C_r x)^2 - (C_t y - C_r y)^2}$;

while $(TargetDistance > 0)$ **do**

    ContextValue = Evaluet $Context(R)$ function ;

    if *(ContextValue=0)* **then**

        Evaluate Obstacle Avoidance Behaviour FIS;

    else

        Evaluate Target Tracking Behaviour FIS;

    end

    $TargetDistance = \sqrt{(C_t x - C_r x)^2 - (C_t y - C_r y)^2}$;

end

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using a team of Pioneer P3DX robots in an enclosed space with dimension 40 x 25 meters included fixed obstacles. The figure Fig 4 shows the environment that we have used to test the proposed architecture. We have realized several simulations with different configurations. In figure Fig 4.(a) we have simulated a robot that has broken down, the traces of movement of the active robot show that the latter considered the failed robot as a fixed obstacle. In figure Fig 4.(b) we have realized the same simulation, but we have turned on two robots simultaneously. The traces show that the two robots have not been intersected and the figures Fig 4.(c) show that the robot paths cross in the two points A and B. The mechanism of selection behaviours makes it possible to avoid the collisions. Finally, the figure Fig 4.(d) clearly shows that robots always arrive at the target without collision with any obstacles or with another robot.

Fig. 4: Paths generated by combination behaviours process in navigation multi robots system

5 Conclusion

Fuzzy logic can be a useful tool for the navigation process in the distributed MRS and more particularly in a dynamic and uncertain environment. It can be used to formulate the different information received and observed by robots in the form of linguistic terms similar to those used by human. From this point of view, we can design robots with reasoning abilities which are similar to those found in humans. This may be possible if we choose a set of rules that allow the use these linguistic variables to conclude other information in order to make a particular decision. For this, it is necessary to use an appropriate architecture, especially when the functionalities of the robots are effectively separated. The process of selection behaviours proposed shows a great flexibility to implement the different navigation approaches in multi-robot systems.

Competing interests

The authors declare that they have no competing interests.

Authors' contributions

All authors have contributed to all parts of the article. All authors read and approved the final manuscript.

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