Real Time Tracking Trajectory and Obstacle Avoidance for Two Mobile Robots by FLC and NMPC

Halim MERABTI[1], Ibrahim ALIOUCHE[2], Abdelkadir BOUHALLIT[2], Khaled BELARBI[2], Hassene NEZZARI[1], Abdessalem BENAMMAR[1]

[1]Research Center in Industrial Technologies CRTI, Algiers, Algeria.
[2]Ecole Nationale Polytechnique de Constantine, Electrical Engineering Department, Constantine, Algeria
merabtihalim@yahoo.fr

Abstract: Fast solution procedures are still persist as a challenge for autonomous mobile robot control for tracking trajectory, while simultaneously detecting and avoiding static and dynamic obstacles. In this work, two fast controllers are investigated: the Fuzzy Logic Controller (FLC) and the NMPC based on the Knowledge Particle Swarm Optimization (KPSO). Theses controllers are used to control two mobile robots at the same time for trajectory tracking and obstacle avoidance in a dynamical environment. Simulation and experimental results are presented for the studied controllers. The results show that the FLC has the fastest computation time with an acceptable accuracy in tracking trajectory and obstacle avoidance while the control signals smoothness and robots navigation accuracy are very good with the NMPC-KPSO. In this latter case, the computation of the control signal needs to be shortened.

Keywords: Nonlinear model predictive control, Mobile robots, tracking trajectory, Fuzzy logic control.

1. Introduction

Today, wheeled mobile robots are being applied in many sectors such as defense, transport, industry. Indeed, the mobile robot can execute many tasks like exploration, material manipulation, patrolling, etc. Therefore, a high performance robots control is required that permits a good traveling in various static and dynamic environments. Advanced control algorithms were applied to enhance robots performance. For example, the sliding mode control (SMC) law was used to stabilizing a non-holonomic wheeled mobile robot to a desired trajectory (Yang, J. M., J. H. Kim. 1999) and in (Rossomando, F. G., C. Soria, R. Carelli, 2014) a sliding mode control method based on adaptive neural networks was proposed for a non-holonomic mobile robot where the authors combine feedback linearization with a practical design to compensate the dynamics of the robot. The main advantages of using SMC are the fast response, robustness, and a relative simplicity of design.

The Fuzzy Logic Controller, FLC, is a robust and intelligent control method which has been applied efficiently in mobile robot motion control. Usually, two fuzzy logic controllers are implemented for mobile robot navigation, one to navigate the robot to its target and the other for obstacle avoidance. However, recently a fuzzy logic controller was proposed in (Xi, L., B. J. Choi, 2013) to control an indoor mobile robot for path tracking with obstacle avoidance. In (Masmoudi et al. 2016) a fuzzy logic PI controller was designed for an intelligent navigation algorithm for omnidirectional mobile robots.

On the other hand and due to its simplicity, classical control such as PID has also been considered for mobile robot control. For instance, in (Padhy et al. 2010) a new approach based on a PID controller was presented for stable trajectory tracking of a non-holonomic wheeled mobile robot.

However, most algorithms do not take into account actuators constraints explicitly and proceed by saturation and because of the dynamics of the environment the reference trajectory must be computed online for the next few steps.

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The basic features of the Model Predictive Control (MPC) are that allows the online computing of the reference trajectory and taking into account actuators constraints in the problem definition (Maciejowski 2001, Mayne et al. 2000).

On the other hand, the main problem for its application to the control of wheeled mobile robots is associated to the important computation time related with optimization problems to be resolved at every sampling period. In order to alleviate this problem, two approaches were proposed. The first approach consists in the implementation of the MPC algorithm on field programmable gate arrays (FPGAs). In (Juan et al. 2014), the authors have presented the use of FPGAs for efficient MPC implementations and in (Lucia et al. 2017) authors have proposed an approach to reach an optimized software-supported implementation of model predictive controller on field programmable gate arrays (FPGAs). In the second approach various algorithms have been proposed. In (Bemporad et al 2000), the control law is computed offline and the controller is implemented online as a lookup table and in (Wang, Y., S. Boyd, 2010), the authors have presented a collection of methods to reduce the computation time of the MPC by exploiting the particular structure of its problem where the control signal is computed faster than methods that use a classical optimizer.

In (Yingbai Hu et al. 2021) a varying-parameter one-layer projection neural network is used to solve a quadratic programming optimization problem of the NMPC to control a mobile medical robot. In (Merabti et al.2016), particle swarm optimization (PSO), and gravitational search algorithm (GSA) have been applied to resolve the optimization problem of the NMPC to control a wheeled mobile robot while in (Kanungo et al.2021) ant colony optimization algorithm (ACO) was applied to solve the MPC optimization problem to control the torque of a three-phase induction motor.

In this work, we analyze the performance of two control algorithms for trajectory tracking and obstacle avoidance for mobile robots in a dynamic environment. We consider the fuzzy logic controller, FLC, and the nonlinear model predictive controller based on the Knowledge based PSO, KPSO. These controllers are used to control the position and the orientation of the robot in the same time.

This paper is organized as follows: the second section gives the Kinematical model of the mobile robots used in this work; the third section presents the controllers used to control the mobile robots. In the fourth section, simulation results are presented. The fifth section presents the experimental results and the conclusion is given in the last section.

2. Kinematical model of wheeled mobile robot

Two real wheeled mobile robots are considered (figure 1). Each real robot tracks a virtual one. Robots Kinematical model is given by:

$$\dot{x}_i(t) = \frac{v_{ri}(t)+v_{li}(t)}{2} \cos\theta_i(t) \tag{1}$$

$$\dot{y}_i(t) = \frac{v_{ri}(t)+v_{li}(t)}{2} \sin\theta_i(t) \tag{2}$$

$$\omega_i = (v_{ri} - v_{li}/b) \tag{3}$$

$$v_i = (v_{ri} + v_{li}/2) \tag{4}$$

v_{r1}, v_{r2} : right wheels linear velocities.

v_{l1}, v_{l2} : left wheels linear velocities,

$b \in R$: distance between the centers of the wheels.

$\theta_{1,}$, θ_2: robots orientations.

ω_1, ω_2 : angular velocities.

The problem is to determine the control signals described by $[v_{r1}(t), v_{l1}(t), v_{r2}(t), v_{l2}(t)]$ that permits the robots to track the reference trajectories given by: $[x_{r1}(t) \;\; y_{r1}(t)]$ $[x_{r2}(t) \;\; y_{r2}(t)]$ using nonlinear model based predictive controller and fuzzy logic controller.

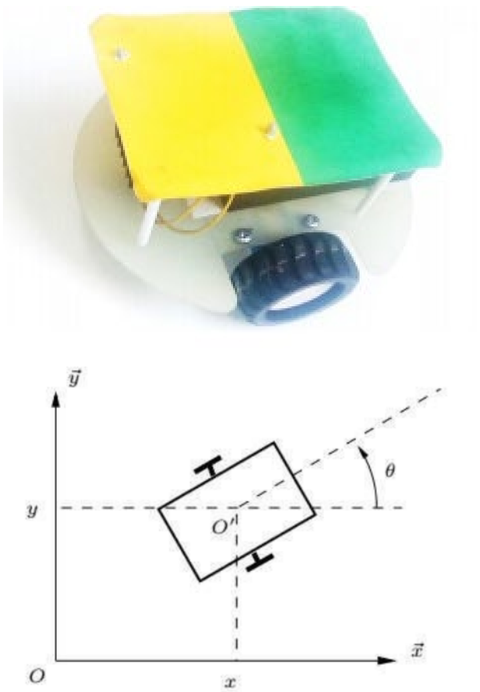


Figure 1. Controlled robot

3. Studied Controllers

In this part, we present the control schemes used in this work for mobile robots tracking trajectories and obstacles avoidance.

A. Fuzzy logic controller, FLC

A Mamdani fuzzy logic controller is used to control the mobile robot for trajectory tracking and obstacle avoidance. Position error and orientation error are the inputs of the FLC. Right and left wheel velocities are the outputs of the FLC. In this work, only one controller is used to control position and orientation of the mobile robot.

$$d = \sqrt{(x_d - x_r)^2 + (y_d - y_r)^2} \tag{5}$$

$$\theta_r = atan2(\frac{y_d - y_r}{d}, \frac{x_d - x_r}{d}) \tag{6}$$

$$\varphi = \theta_d - \theta_r \tag{7}$$

(x_d, y_d, θ_d): desired position and orientation
(x_r, y_r, θ_r): robot position and orientation
d: position error;
φ: orientation error.

The output of the fuzzy controller is given by:

$$z = \frac{\sum_{i=1}^{m} z_i \mu(z_i)}{\sum_{i=1}^{m} \mu(z_i)} \tag{8}$$

Where:
z: is the output of the Fuzzy Logic Controller (v_r, v_l)
$\mu(z_i)$: is the membership function
In this work, the output of the FLC is computed using the gravity center method.

The Fuzzy membership functions are used to convert the crisp inputs provided to the fuzzy inference system. It specifies the degree to which a given input belongs to a set (Fuzzification).

Then the rules are evaluated and combined in the rule base of the FLC (inference system). Finally, the output data is converted to a crisp output (defuzzification) (as in figure 2).

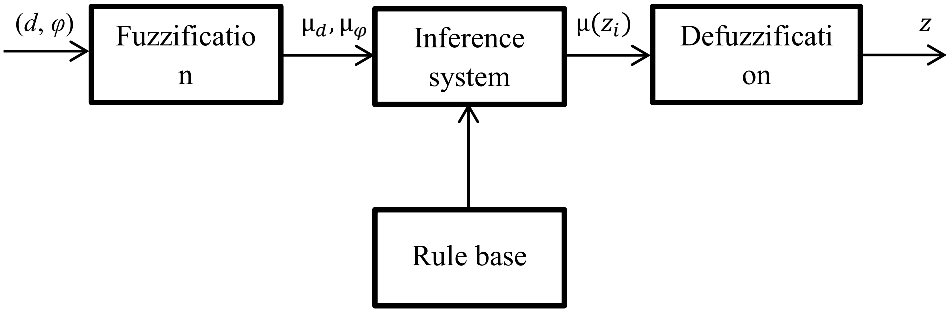


Figure 2. Fuzzy logic controller scheme

To avoid the collision between the robot and the obstacle, the orientation error is changed as follow:

$$\phi_{obs} = \theta_{obs} + \theta_{dev} \tag{9}$$

θ_{dev} : is the deviation angle which is chosen as:

$$\theta_{dev} = \frac{\pi}{2} \times \frac{1-d_{obs}}{r} \tag{10}$$

d_{obs} : is the distance between the robot and the obstacle.
r *:* the safe distance between the robot and the obstacle.
To avoid the obstacle the parameter $sign(\psi)$ is used which is given by:

$$sign(\psi) = \begin{cases} 1 & si\psi = 0 \\ \frac{\theta_d - \theta_{obs}}{|\theta_d - \theta_{obs}|} sinon \end{cases} \tag{11}$$

$$\phi_{obs} = \theta_{obs} + sign(\psi) \times \frac{\pi}{2} \times \frac{1-d_{obs}}{r} \tag{12}$$

B. Nonlinear model predictive controller based on the KPSO
B.1. Nonlinear model predictive controller
Consider a robotic system, the discrete state space model has the following form:

$$\boldsymbol{x}_{k+1} = f(\boldsymbol{x}_k,\ \boldsymbol{u}_k), \tag{13}$$

where:
x : is the constrained state space into a convex and closed set as:

$$\boldsymbol{x}_k \in \mathbb{X} \tag{14}$$

$\boldsymbol{u}$ *:* is the control signal constrained as:

$$\boldsymbol{u}_k \in \mathbb{U} \subset \mathbb{R}^m \tag{15}$$

and $f(\boldsymbol{x}_k,\ \boldsymbol{u}_k)$ is a continuous mapping with $f(\boldsymbol{0},\ \boldsymbol{0}) = 0$ ..

To regulate the state to the origin space using the NMPC, the optimization problem to be resolved can be given as follows:

$$\xi_N(\boldsymbol{x}, k, \mathcal{U}) = L(\boldsymbol{x}_{k+N}) + \sum_{i=k}^{k+N-1} F(\boldsymbol{x}_i, \boldsymbol{u}_i). \tag{16}$$

Where $L(\boldsymbol{x}_{k+N})$ is the weight on the final state space. *N* is the prediction horizon. The weight *L* and the final region are introduced to guarantee stability of the NMPC and the final state may be constrained to be in a final region:

$$\boldsymbol{x}_{k+N} \in \mathrm{X}_f \subset \mathbb{X}. \tag{17}$$

At each sampling, the optimal solution is given as an optimal sequence:

$$\mathcal{U} = [\boldsymbol{u}_k \quad \boldsymbol{u}_{k+1} \quad \cdots \quad \boldsymbol{u}_{k+N-1}] \in \mathbb{U}^N, \tag{18}$$

and only the first element of the sequence is applied to control the robot at the sampling time *k*.
The resolution of the non-convex optimization problem described in (16) allows the

computation of the control signals across to the prediction horizon and ensure an accurate tracking of the reference trajectory. Recently, Metaheuristics such as, particle swarm optimization (PSO), ant colony optimization (ACO) were used to solve difficult optimization problems in a reasonable computing time (Huang, Xu, and Hsu 2014b; Huang et al. 2014a).

B.2. Knowledge-based Particle Swarm Optimization

We consider the use of the Knowledge based Particle Swarm Optimization algorithm, KPSO, for the solution of NMPC as in (Merabti et al. 2016) and (Merabti, H., K.Belarbi. 2017).

The particle swarm optimization (PSO) algorithm inspired by the behaviour of organisms that live and interact within large groups (Zietkiewicz et al, 2020). This metaheuristics has a few adjustable parameters and converge faster than various global optimization algorithms. In each iteration, positions of the particles are updated basing on the local best position p_k^i and the global best position p_k^g. Particles positions and velocities are updated using the following equations:

$$v_{k+1}^i = v_k^i + c_1 r_1\left(p_k^i - x_k^i\right) + c_2 r_2 (p_k^g - x_k^i), \tag{19}$$

$$x_{k+1}^i = x_k^i + v_{k+1}^i. \tag{20}$$

Where: x_k^i and v_k^i are the position and the velocity of the particle, respectively; p_k^g and p_k^i are the global best and local best positions, respectively; c_1, c_2 : Constants; r_1, r_2 : Random numbers between 0 and 1.

A prior knowledge of the best solutions allows the metaheuristic algorithm to reduce the computation time and increase the solution precision.

4. Application

In this part, the studied controllers (FLC and NMPC) are applied and compared to control two wheeled mobile robots for tracking trajectories and obstacles avoidance. At each sampling period we record the computation time to find the control signals. The calculator used in this work is an Intel® Core™ i7 at 2.4 GHz with 8Go RAM.

A. Problem setting

The objective is to find the control signals given by $[v_{r1}(t), v_{l1}(t), v_{r2}(t), v_{l2}(t)]$ that permits the robots to track a reference trajectories given by: $[x_{d1}(t) \quad y_{d1}(t)]$ and $x_{d2}(t) \quad y_{d2}(t)]$ and avoid static and dynamic obstacles.

The reference trajectory for the first robot is given by:

$$x_{d1}(t) = \cos(\omega_0 t)\,;\ y_{d1}(t) = \sin(2 * \omega_0 t) \tag{21}$$

The reference trajectory for the second is given by:

$$x_{d2}(t) = \cos(\omega_0 t + \varphi)\,;\ y_{d2}(t) = \sin(2 * \omega_0 t) \text{ and } \omega_0 \ = \ 0.02\text{rad/s}. \tag{22}$$

B. Simulation results

In this part, the FLC and the NMPC controllers are applied to control two mobile robots for tracking trajectory and obstacle avoidance

B.1. Fuzzy logic controller

The position and angular errors are used as the inputs of our Fuzzy Logic Controller where the right and left wheels linear velocities are the outputs of the FLC. Figure 3, 4 and 5 give the membership functions of the input and output variables and their distribution on respective universe of discourses with:

$$a_1 = 0, a_2 = 0.1, a_3 = 0.3; \tag{23}$$

$$b_1 = -\frac{\pi}{4}, b_2 = 0\,, b_3 = \frac{\pi}{4}\,; \tag{24}$$

$$c_1 = 0\,, c_2 = 0.1\,, c_3 = 0.3, \tag{25}$$

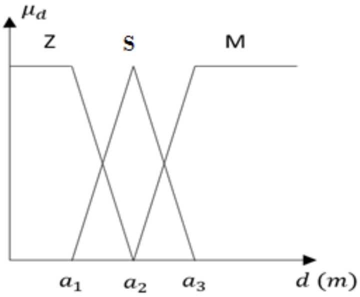


Figure 3. Membership function (a) Position error

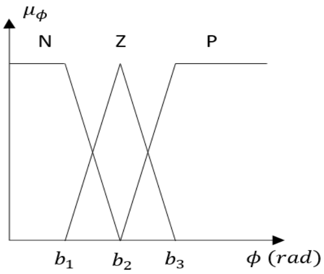


Figure 4. Membership function (b) Angular error

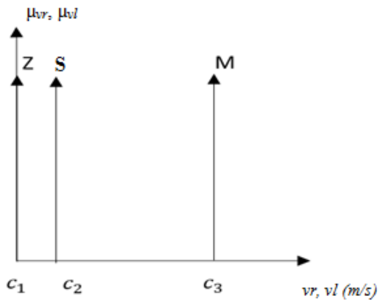


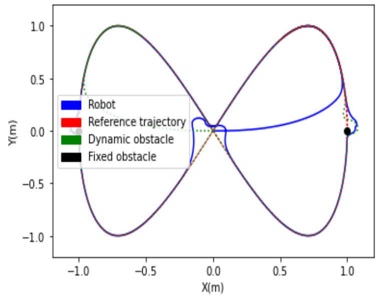
Figure 5. Membership function (c) Control signals

Table I gives the rule base.

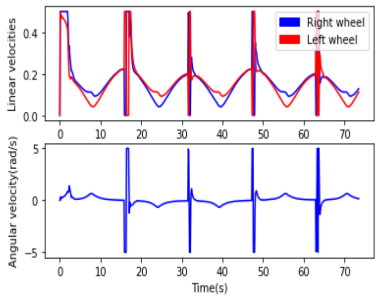
Table 1. The rule base of the FLC

	Angular error	N		Z		P	
		V_r	V_l	V_r	V_l	V_r	V_l
position error	Z	S	Z	Z	Z	Z	S
	S	M	Z	S	S	Z	M
	M	M	Z	M	M	Z	M

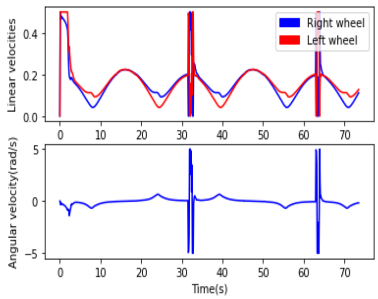
The results of the application of the FLC controller for tracking trajectory and obstacles avoidance are given in Figures 6(a), 6(b) and 6(c). These figures show the good tracking of the reference trajectories by the robots (position and orientation) and the success to avoid static obstacles. The robots have succeeded also to avoid collision between them. The control signals are slightly active but can be smoothed by increasing the number of rules. Control signals are obtained after 30µs.



(a)



(b)



(c)

Figure 6. Simulation results by FLC (a) Robots trajectories by the FLC, (b) Linear and angular velocities of the first robot by the FLC, (c) Linear and angular velocities of the second robot by the FLC.

B.2. Nonlinear model predictive controller

The NMPC optimisation problem is given by:

$$min\ \xi_i = min(\sum_{k=1}^{N}(x_i(t+k) - x_{di}(t+k))^2 + (y_i(t+k) - y_{di}(t+k))^2 + r_1 {v_{ri}}^2(t+k) + r_2 {v_{li}}^2(t+k)). \qquad (26)$$

Under the constraints:

$$-0.5(m/s) \leq v_{ri} \leq 0.5\ (m/s), \qquad (27)$$

$$-0.5(m/s) \leq v_{li} \leq 0.5(m/s). \qquad (28)$$

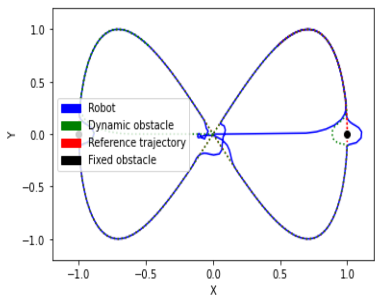
At any sampling time, the optimization problem described by (26) is resolved to find the sequences $v_{ri}(t+k)$ and $v_{li}(t+k)$ k=1...N. Only $v_{ri}(t)$ and $v_{li}(t)$ are applied to the robots.

Table 2. Parameters of the NMPC-KPSO

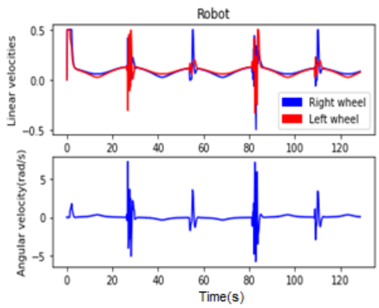
Prediction horizon N	Swarm size	Iterations	Correction factor	inertia
06	20	20	1.2	0.8

The KPSO is used to resolve this constrained non convex optimization problem.

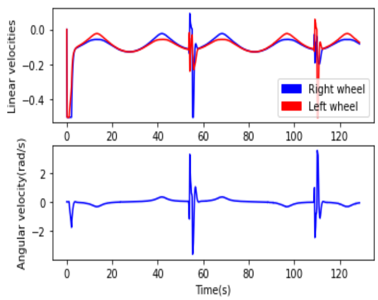
The constrained optimization problem is transformed into an unconstrained one using the method of penalty. The penalty function of the constraints is added to the cost function (Nocedal and Wright 2006). In the NMPC scheme the tracking is ensured by the resolution of (26) and the static and dynamic obstacles avoidance is ensured by adding a penalty to the cost function if the distance between the robot and the obstacle is less than the safe distance.



(a).



(b).



(c)

Figure 7. Simulation results by NMPC-KPSO (a) Robots trajectories by the NMPC-KPSO, (b) Linear and angular velocities of the first robot by the NMPC-KPSO, (c) Linear and angular velocities of the second robot by the NMPC-KPSO.

The results of the application of the NMPC for tracking trajectories and obstacles avoidance are given in Figures 7(a), 7(b) and 7(c). Through figures it can be seen the good tracking of the reference trajectories by the robots and the success to avoid obstacles and robot collision. Control signals are obtained after 100µs.

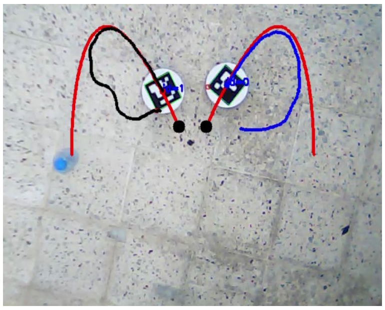
Figures show the capability of the investigated controllers to drive the mobile robots to track the reference trajectories and avoid both static and moving obstacles. We can observe that the robots recover the reference trajectories rapidly and the tracking by the NMPC and the FLC is stable and the avoidance of the obstacles is very clear.

C. Experimental results

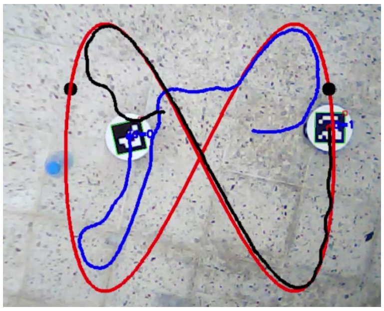
After the above results which show that the FLC and NMPC-KPSO are feasible for real time applications, we have applied both controllers for wheeled mobile robots tracking trajectories and obstacles avoidance. The robots used in these experiments are two-wheel robots, each one is constructed using an Arduino Nano and two DC motors. Two Arduino Uno cards ensure the wireless communication between the robots and the PC. They transmit the control signal values from the PC to the robots using the NRF24L01. Each robot is equipped by another NRF24L01 linked to the Arduino Nano. After decoding, the control signals are transmitted to the L298n driver to control the motors. A camera is used to track the robots positions and orientations.

C.1. Fuzzy logic controller

The reference trajectories are given by equations (21) and (22). The results are shown in Figure 8(a), 8(b), 8(c), 8(d) and 8(e) where it can be seen that the robot tracks the reference trajectories. These results show the good quality of the tracking.



(a).



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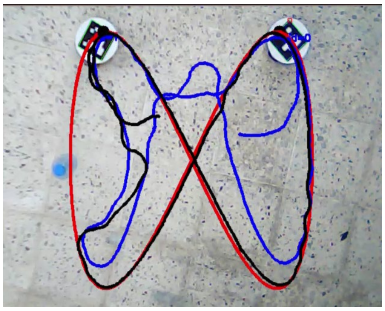

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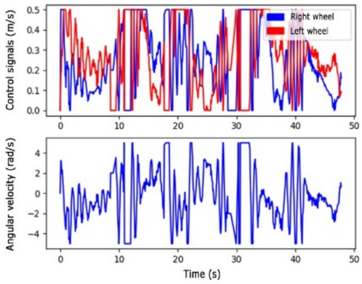
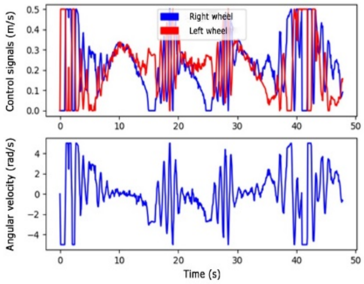


(d)



(e)

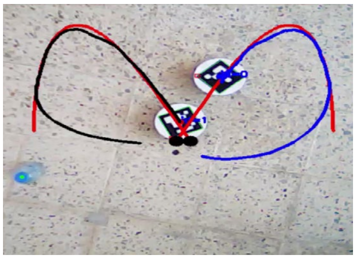
Figure 8. Experimental results by FLC: Robots trajectories (a) Tracking trajectories and avoiding collision, (b) Tracking trajectories and avoiding fixed obstacle, (c) All trajectories, (d) Linear and angular velocities of the first robot by the FLC, (e) Linear and angular velocities of the second robot (obstacle) by the FLC

C.2. Nonlinear model predictive controller

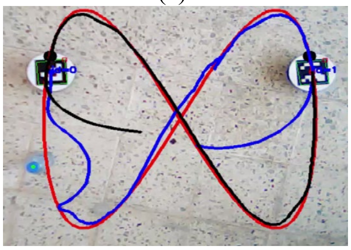
The results are shown in Figure 9(a), 9(b), 9(c), 9(d) and 9(e) where it can be seen the high quality of the tracking.

The experimental results obtained by applying the FLC and NMPC controllers for tracking trajectories are encouraging. Although, it can be seen that the quality of tracking and the avoidance by the NMPC is better than by the FLC where the computation time by the FLC is shorter. In addition, it can be observed that smoothness of the control signals (Minimum energy dissipation criterion), computed by the NMPC is better than there computed by the FLC, which can be improved by increasing the number of rules. These results confirm the simulation ones.

On the other hand, the NMPC-KPSO represents a compromise solution to the multi-objective problem: minimum computation time and high quality of the control signals. Where in (Merabti et al 2016) the computation time was of the order of few milliseconds with high quality of the control signals. However, in (Merabti, H., K.Belarbi. 2017), the computation time was a few microseconds with an active control signals. The experimental results presented in this paper are better than thoses presented in (Merabti et al 2016) and (Merabti, H., K.Belarbi. 2017).



(a).



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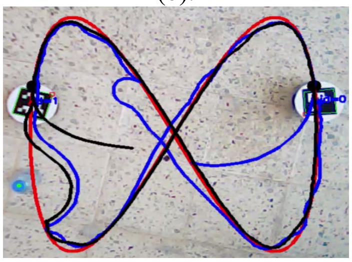

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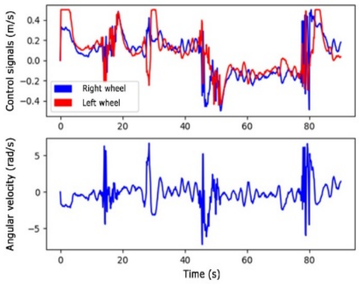

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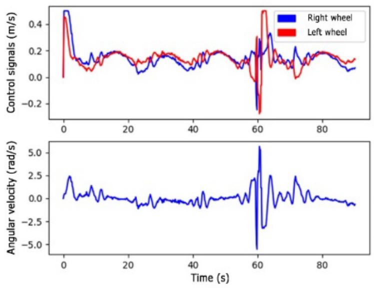

(e).

Figure 9. Experimental results by NMPC-KPSO: Robots trajectories (a) Tracking trajectories and avoiding collision, (b) Tracking trajectories and avoiding fixed obstacle, (c) All trajectories, (d) Linear and angular velocities of the first robot by the NMPC-KPSO, (e) Linear and angular velocities of the second robot (obstacle) by the NMPC-KPSO

6. Conclusion

In this work, we have investigated two control schemes for mobile robot trajectory tracking and avoiding fixed and dynamical obstacles: the FLC and the NMPC-KPS. Simulation and experimental studies were carried out for tracking trajectories with fixed and dynamic obstacles. The obtained results show that the tracking trajectory and the obstacle avoidance are better by the NMPC-KPSO with an acceptable computation time. On the other hand, the FLC has faster computation time with acceptable robot navigation. Both controllers have proved there capability to control mobiles robots for tracking trajectories and obstacles avoidance in the same time.

Nomenclature

c_1	cognitive learning, constant
c_2	social learning, , constant
L	weight on the final state
ξ_N	optimization problem
(x_d, y_d, θ_d)	desired position and orientation
(x_r, y_r, θ_r)	robot position and orientation
N	prediction horizon
p_k^i	local best position;
p_k^g	global best position;
r_1, r_2	random numbers ϵ [0,1]
θ	robot orientation
u_k	control signal
v_k^i	particle velocity
x_k^i	particle position;
θ_{dev}	deviation angle
$\mu(z_i)$	membership function
z	output of the FLC
r	safe distance between the robot and the obstacle

7. References

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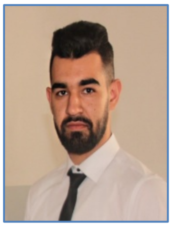
Halim MERABTI, Received the Engineer Degree in electrical engineering from Constantine University, Constantine, Algeria. He received the Ph.D. Degree in electronics, in 2015, from Constantine University. He currently holds the position of senior researcher A in Research Center in Industrial Technologies (CRTI), Algeria. His research interests include the control systems, Artificial Intelligence, robotics, computer computation.



Ibrahim ALIOUCHE is an electrical engineering student at the university of Liege, Belgium. Interested in signal processing and intelligent robotics. He received his master's degree in automatics and control engineering from the national polytechnic school of Constantine, Algeria, in 2018.

Abdelkader BOUHALLIT, Received the engineering degree in automation and control systems from the national polytechnic school of Constantine, Algeria in 2018, and the Master degree in industrial robotics from the university of Paris Saclay, France in 2020.
He is interested in automation and control, robotics and computer vision, He's been working as a robotics and automation engineer since 2021."

Khaled BELARBI, Received the “ingenieur” degree from the Ecole Polytechnique of Alger, Algeria, and the MSc. (December1984) and Ph.D. (June 1988) degrees in automatic control from the University of Manchester Institute of Science and Technology, UMIST, U.K. Since 2014, he is a Professor at Ecole Nationale Polytechnique de Constantine, ENPC, Algeria. Before joining ENPC, he was with the department of electronics Faculty of Technology, University of Constantine.

Hassene NEZZARI, Received the Engineer Degree in electrical engineering from Larbi Tebessi University, Tebessa, Algeria. He received the Ph.D. Degree in electronics, in 2013, from Constantine University, Constantine, Algeria. In May 2011, he has joined the Research Center in Industrial Technologies (CRTI), Algeria. He currently holds the position of professor-researcher at Larbi Tebessi University, Tebessa, Algeria. His research interests include the fractional order operators and systems, fractional order signal processing, sensors, Electroacoustic and Microsystems field.

Abdessalem BENAMMAR, Received his diploma of Engineering in Electronic from University of Blida, Algeria in 2000, He received his PHD in Electronic from University of Blida, Algeria in 2010. He is Deputy Director of Research Center in Industrial Technologies -CRTI. His research are based on signal and image processing applied to ultrasonic phased array, guided waves, automatic control and X-ray tomography.