Preprints of the 19th World Congress
The International Federation of Automatic Control
Cape Town, South Africa. August 24-29, 2014

Multi-Robot Systems Formation Control with Obstacle Avoidance

Tiago P. Nascimento, Andre G. S. Conceicao, [**]
António Paulo Moreira [***]

Department of Computer Systems, Informatics Center, Federal University of Paraiba (UFPB), (e-mail: tiagopn@ci.ufpb.br).
[**] Department of Electrical Engineering, Federal University of Bahia, (e-mail: andre.gustavo@ufba.br).
[***] Department of Electrical and Computer Engineering, University of Porto, (e-mail: amoreira@fe.up.pt)

Abstract: This paper deals with the problem of active target tracking with obstacle avoidance for multi-robot systems. A nonlinear model predictive formation control is presented which uses potential functions as terms of the cost function. These terms penalize the proximity with mates and obstacles, splitting the problem of obstacle avoidance into two repulse functions. Experimental results with real robots are presented to demonstrate the performance of the approach.

Keywords: Nonlinear Model Predictive Control, Mobile Robots, Obstacle Avoidance.

1. INTRODUCTION

Motion planning algorithms are widely used nowadays. In areas such as: UAV path planning (Alejo et al. (2009)), mobile robot indoor navigation (Nascimento et al. (2012)), and even in video games (Khantanapoka and Chinnasarn (2009)) path planning algorithms have been conceived to be the solution to many obstacle avoidance issues.

Therefore, many path planning techniques rose over the years. One among the most famous is the artificial potential field approach. This methodology has been used and it states that the collision-free trajectory is generated along the negative gradient of the defined attractive and repulsive potential field functions. The subsequent studies can be found in Yang (2002), and Pathak and Agrawal (2005). Predictive Control and its variants have been widely used in multi-robot systems control, such as leader-following approach (Ribeiro et al. (2013)), decentralized Linear time-varying MPC (Bemporad and Rocchi (2011)), formation control based on attractive potential functions (Hernandez-Martinez and Bricaire (2012)), and formation control with Takagi-Sugeno type fuzzy automaton (Nascimento et al. (2013a)).

In this paper, the problem of Active Target Tracking (ATT) with obstacle avoidance for a formation of mobile robots is tackled by exploiting a Nonlinear Model Predictive Formation Control (NMPFC), previously conceived in Ahmad et al. (2013). The NMPFC is implemented in a distributed fashion, meaning that the cost functions to be minimized by each robot controller are coupled. In this way, the actions and the target observations taken by each robot affect every other component of the multi-robot system. In particular, the problem of obstacles avoidance based on Artificial Potential Field (APF) is examined in details, showing the performance of the approach which uses potential functions as terms of the cost function. Experimental results show the effectiveness of strategy proposed considering the obstacle avoidance problem with two robots and with vision obstruction of the target.

The paper is organized as follows. The omnidirectional robots are described in Section 2. Section 3 the NMPFC proposed is explained. In section 4 the Artificial Potential Field approach used in the cost function of the NMPFC is explained. In section 5 the experimental results are presented and discussed. Finally, the conclusions and future works are drawn in section 6.

2. ROBOT DESCRIPTION

The robots, Fig. 1, are equipped with three omnidirectional wheels connected to geared motors. Each pair wheel-encoder is connected to a controller board. This board has a microcontroller that measures the wheel speed and implements a local controller. This controller maintains the requested speed and is based on PID (Proportional-Integral-Derivative) control. This low level module has a sampling frequency of 100 Hz. The controllers are connected to the PC by a RS-232 link running at 115200 baud. The robot has a standard Notebook (Intel Dual Core 2Ghz/Core with 2Gb RAM) with Ubuntu 9.04. The high level controllers are implemented in Lazarus, it is a component-based development environment for two-way visual development of graphical user interface, internet, database and server applications. Another very important module is the one that deals with the image captured by the onmidirectional vision system and extracts the most important features. This information is used to construct an estimation of the robot position. The vision camera also provides the sample time control of the robot (25 Hz, sample time of 40 milliseconds). Details about the model of these robots can be found in Conceicao et al. (2009).

Fig. 1. Mobile robots.

3. NONLINEAR MODEL PREDICTIVE FORMATION CONTROL

The NMPFC's ability to create and maintain a formation is due to the fact that the cost functions used by the controllers of each robot in the team are coupled. Therefore, the NMPFC is implemented in a distributed fashion (Maestre et al. (2011)). The above mentioned coupling occurs when the teammates' states are used in the cost function of each robot's controller to penalize the geometry or the deviation from the desired objective. This means that the actions of each robot affect every other teammate. Each robot keeps the formation state (pose and speed of the robots in formation, and position and speed of any target that should be followed), updating them in each control loop. This information is received by the controller of each robot in the formation which in turn creates the formation geometry where the actions of each robot affect the other teammates.

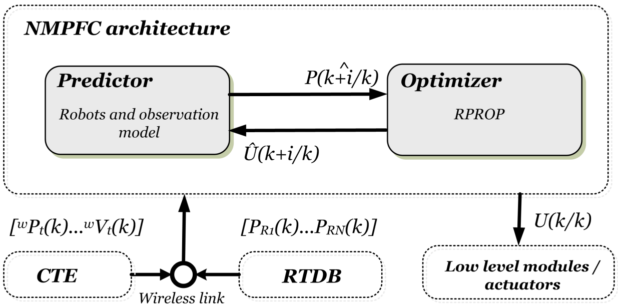


Fig. 2. Controller diagram for each robot.

Fig. 2 illustrates the structure of the NMPFC where $U(k|k) = U(k) = [\, v_{ref}(k) \; vn_{ref}(k) \; w_{ref}(k) \,]^{\mathrm{T}}$ is the output control signal in the first prediction step, $\hat{U}(k+i|k)$ with $i = 0 ... N_c - 1$ is the output control signal from the optimizer sent to the predictor, and $\hat{P}(k+i|k)$ with $i = 1...N_p$ is the response of the predictor block to each $\hat{U}(k+i|k)$. The vector $P_{\mathrm{R}_i}(k) = [\, x_{\mathrm{R}_i}(k) \; y_{\mathrm{R}_i}(k) \; \theta_{\mathrm{R}_i}(k) \,]^{\mathrm{T}}$ represent the robots'pose at instant k. Furthermore, the NMPFC receives the robots' poses $[P_{R_1}(k)...P_{R_N}(k)]$, the position of the target in the world frame ${}^{w}P_{\mathrm{t}}(k) = [\, {}^{w}x_{\mathrm{t}}(k) \; {}^{w}y_{\mathrm{t}}(k) \,]^{\mathrm{T}}$ and the velocity of the target t in the world frame ${}^{w}V_{\mathrm{t}}(k) = [\, {}^{w}v_{x\mathrm{t}}(k) \; {}^{w}v_{y_{\mathrm{t}}}(k) \,]^{\mathrm{T}}$ from the robot's RTDB (Real Time Data Base). Details about the Cooperative Target Estimator (CTE) and the Real Time Data Base (RTDB) can be found in Ahmad and Lima (2011) and Oliveira et al. (2012), respectively.

The sub-block called Predictor performs the state evolution of the robot itself, the teammates and the target based on pre-defined models. Each robot keeps the formation state (pose and speed of the robots in formation, and position and speed of any target that should be followed), updating them in each control loop. The sub-block called Optimizer uses an on-line numeric optimization method to minimize the cost function and to generate the signals of the optimal control. The resilient propagation (RPROP) method is used here and it guarantees a swift convergence. To overcome the inherent disadvantages of pure gradient-descent, the RPROP performs a local adaptation of the weight-updates according to the behavior of the error function.

3.1 The Cost Function

The cost function of a NMPC (here NMPFC) represents the cost to be minimized by the predictive controller. It is typically associated with the dynamic changing of the system (formation geometry) over time. The desired formation for the robots to be around the target in a way to better estimate the target's velocity possesses the following characteristics:

- Minimize the total amount of uncertainty;
- The robots must maintain a threshold distance D_{val}, from the target;
- The robots must maintain a desired orientation around the target;
- The robots must not collide between them, with an obstacle or with the target.

The cost function (Ahmad et al. (2013)), embedded in all robots, is as follows :

$$\begin{aligned} J(N_1, N_p, N_c) = & \sum_{i=N_1}^{N_p} \lambda_a |det(\Sigma^{\perp}_{\mathrm{Merged}}(k+i))| + \\ & \sum_{i=N_1}^{N_p} \lambda_0 |(D_{val} - ||P_{\mathrm{t}}^{\mathrm{R}_n}(k+i)||)| + \\ & \sum_{i=N_1}^{N_p} \lambda_1 |\delta(\theta_{\mathrm{R}_n}(k), \theta_{\mathrm{t}}^{\mathrm{R}_n}(k+i))| + \\ & \sum_{i=N_1}^{N_p} \lambda_2 |P_{val} + (\tilde{P}_{\mathrm{t}}^{\mathrm{R}_n}(k+i) \cdot \tilde{V}_t(k+i))| + \\ & \sum_{i=N_1}^{N_p} \sum_{j=1}^{NM} \lambda_3 \max(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{R}_j}(k+i)||}{D_M}, 0) + \\ & \sum_{i=N_1}^{N_p} \sum_{l=1}^{NO} \lambda_4 \max(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)||}{D_O}, 0) + \\ & \sum_{i=1}^{N_c} \lambda_5 |\Delta U(k+i-1)| \end{aligned} \quad (1)$$

where N_1, N_p are the predicted horizon limits in discrete time. N_c is the control horizon. λ_a, λ_0, λ_1, λ_2, λ_3, λ_4 and λ_5 are the weights for each component of the cost function. $\Sigma^{\perp}_{\mathrm{Merged}}$ is the formation team's merged target observation covariance matrix. D_{val} is the threshold distance between the robot and the ball. P_{val} is the position coefficient which puts the robot around the ball in a determined position. $\Delta U(k+i-1)$ is the variation of the control signals, where $U(k)$ is the velocity vector of the robot's frame. Finally, it is important to remember that here $|\cdot|$ denotes 1-norm for vector arguments and absolute value for scalars as well as $||\cdot||$ represents the euclidean norm.

4. POTENTIAL FIELD APPROACH IN NMPFC

The obstacle avoidance approach that most rapidly and easily fits into the optimal control group is the artificial potential fields (APF) approach. In Camacho and Bordons (2004), the author uses the APF embedded in a nonlinear model predictive controller as an example for avoid static obstacles. The potential field approach uses a potential function to navigate the robot (attraction function) that drives the robot towards the target, and an avoidance function (repulse function) that repels the robot when it is near an obstacle. If the NMPFC is considered, then the attraction function could be seen as the first and second terms of the NMPFC cost function in equation 1. Therefore, a repulse function had to be made in order to consider the obstacle avoidance problem.

The main idea underlying the definition of the repulsive potential is to create a potential barrier around the obstacle region that cannot be traversed by the robots' configuration (Latombe (1991)). In addition, it is usually desirable that the repulsive potential does not affect the motion of the robot when it is sufficiently far away from the obstacles. One way to achieve these constraints is to define the repulsive potential function as follows:

$$U_{rep}(q) = \begin{cases} \frac{1}{2}\eta(\frac{1}{\rho(q)} - \frac{1}{\rho_0})^2 \text{ if } & \rho(q) \leq \rho_0 \\ 0 \text{ if } & \rho(q) > \rho_0 \end{cases} \tag{2}$$

where η is a positive scaling factor, $\rho(q)$ denotes the distance from q to the obstacle region (CB), i.e.:

$$\rho(q) = \min_{q' \in CB} ||q - q'|| \tag{3}$$

and ρ_0 is a positive constant called the distance of influence of the obstacles. The function U_{rep} is positive or null, it tends to infinity as q gets closer to the obstacle region, and is null when the distance of the robots' configuration to the obstacle region is grater then ρ_0.

This paper divided the problem of obstacle avoidance in two repulse functions. The first considers the mate avoidance, preventing the robots from colliding with themselves. The second function considers the obstacle avoidance, preventing the robots from colliding with static or moving obstacles which may, or may not appear.

4.1 Mate Avoidance Function

The first idea of a term in a nonlinear model predictive controller that penalizes the approximation between robots in a formation was presented in Nascimento et al. (2013b). In his work, the authors created a sub-function in their nonlinear model predictive controller such as in the equation (4).

$$\sum_{i=N_1}^{N_p} \lambda_3((\frac{1}{||P^{\mathrm{R}_{m1}}_{\mathrm{R}_n}(k+i)|| - D_M})^2 + +(\frac{1}{||P^{\mathrm{R}_{m2}}_{\mathrm{R}_n}(k+i)|| - D_M})^2) \tag{4}$$

Where $||P^{\mathrm{R}_{m1}}_{\mathrm{R}_n}(k+i)||$ is the distance between robot R_n and the mate 1. This function has a nonlinear decreasing behavior as shown in Fig. 3

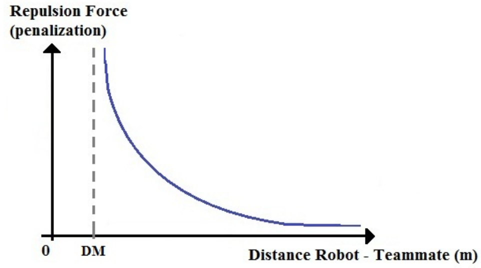


Fig. 3. Behavior of function in 4

As it can be noticed, the first problem is that this approach does not consider a generalized number of mates, only two. However, a more important issue is addressed when analyzing the behavior of this function. The avoidance function for its nonlinearity, takes more time to increase the penalization by proximity, allowing the robots to get too near each other before penalizing it.

A simple solution is proposed here to avoid these problems. The proposed function for mate avoidance can be seen in equation (5).

$$\sum_{i=N_1}^{N_p} \sum_{j=1}^{NM} \lambda_3 \times \max(1 - \frac{||P^{\mathrm{R}_j}_{\mathrm{R}_n}(k+i)||}{D_M}, 0) \tag{5}$$

Noticing that NM is the maximum number of mates, $||P^{\mathrm{R}_j}_{\mathrm{R}_n}(k+i)||$ is the distance between robot R_n and the mate R_j and DM is the given value where small distances are not penalized. The proposed function was changed to a linear function which increases the penalization with proximity much more rapidly. The generalization of mates was also considered with a second sum that gives scalability to the NMPFC controller in this study.

Finally, an extreme case had to be considered when using potential functions. This extreme case, also studied among the potential field approach, takes into account the possibility of the robots being too close to each other much more rapidly then allowed. This behavior can occur if the robots are moving in high velocities for instance. To avoid collision in these cases a protection zone was created around the robots where the weights (λ_1 and λ_3) of the attraction and repulsion functions (terms of the NMPFC cost function) are rapidly switched so the robot gives priority to penalize the mate avoidance rather then get to the target. When the robots are outside this zone once again, the weights of the cost function are set back to the initial values.

4.2 Obstacle Avoidance Function

An obstacle avoidance function was created based on the idea of mates avoidance function and the potential field approach. The repulsion function proposed in this paper can be seen in equation (6).

$$\sum_{i=N_1}^{N_p} \sum_{l=1}^{NO} \lambda_4 \times \max\left(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)||}{D_O}, 0\right) \quad (6)$$

Remembering also that NO is the maximum number of obstacles, $||P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)||$ is the distance between robot R_n and the obstacle O_l and DO is similar to DM.

This function's behavior is similar to the function proposed in the mate avoidance problem. In the obstacle avoidance proposed function, all obstacles (static or moving) are considered to be stopped during the 40ms loop control. This assumption speeds up the calculations in the prediction of the NMPFC by calculating only the robot-obstacle distance evolution in a simplified fashion.

Finally, the same consideration made in the mate avoidance function has to be considered here by creating a security zone. An obstacle can appear in the visible zone towards the robot too rapidly for the robot to avoid it. To avoid collision in these cases a protection zone is created around the robots where the weight of the attraction and repulsion functions (terms of the NMPFC cost function) are rapidly switched so the robot gives priority to penalize the mate avoidance rather then get to the target. When the robots are outside this zone once again, the weights of the cost function are set back to normal.

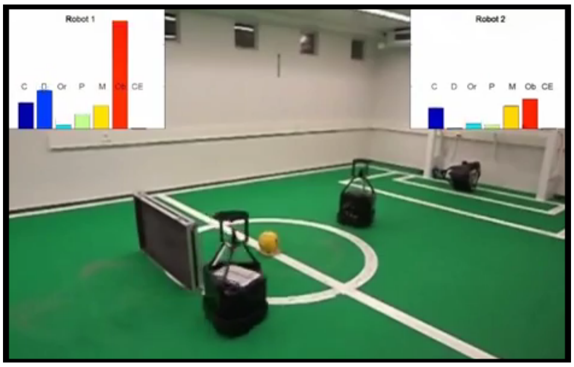
5. RESULTS

A setup, to perform the experiment, was created in order to analyze the behavior of two omnidirectional mobile robots with the NMPFC. Each robot had a computer, a Notebook (Intel Dual Core 2Ghz/Core with 2Gb RAM) with Ubuntu 9.04, running its own NMPFC, CTE and RTDB applications previously seen in Fig. 2. There has been used the following weight values: $\lambda_a = 505$, $\lambda_0 = 918$, $\lambda_1 = 297$, $\lambda_2 = 510$, $\lambda_3 = 500$, $\lambda_4 = 500$, $\lambda_5 = 5.00$. The control horizon was $N_c = 2$ and the prediction limits were $N_1 = 1$ and $N_2 = 7$.

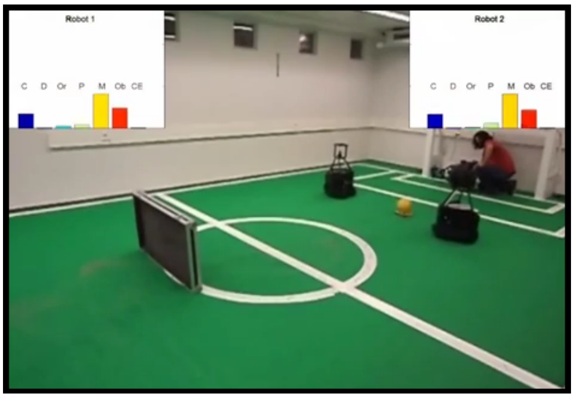
This experiment addresses the obstacle avoidance problem with vision obstruction to the target, where the robot 1 has to avoid an I shape obstacle (wall) as presented in Fig. 4(a). As robot 2 is near the target and it does not have any vision obstruction, it sends the information with the target's position to the robot 1. Therefore, the objective here is to converge to the target departing from the coordinates (2.2,-0.2), (-1.5,-0.2) and (0,-0.2) for the robots 1, 2 and the target(ball), respectively. Then, the NMPFC attracts both robots to the desired distance. The potential function performs a important role in the mates avoidance as well as the obstacle avoidance.

Results show that robot 1 was successful in avoiding the wall, both robots converge to a equilibrium position avoiding collision between them, the target and the wall. This is better noticed on the video available online at: `http://youtu.be/kiqi-Cq1zhs`. The description of the terms of the cost function showed on video are: C (covariance), D (distance), Or (Orientation), P (Position), M (mate avoidance), Ob (Obstacle avoidance) and CE (Control Effort). Fig. 4(b) shows a snapshot of the referred video at instant 3 seconds, and Fig. 4(c) shows the robots at final position.

(a) Initial Position.



(b) Snapshot - 3 seconds.



(c) Final Position.

Fig. 4. Environment and Plot XY.

Fig. 5 shows the trajectories performed by the robots, as well as the perception of the target by the robots.

Fig. 6 shows the behaviour of the potential functions as terms of the cost function during the experiment. Fig. 6(a) shows the evolution over time of the Obstacle avoidance term, Fig. 6(b) shows the mate avoidance term and Fig. 6(c) shows all terms. We can see a clear influence of the Obstacle term in the objective function of the robot 1, due to its initial position.

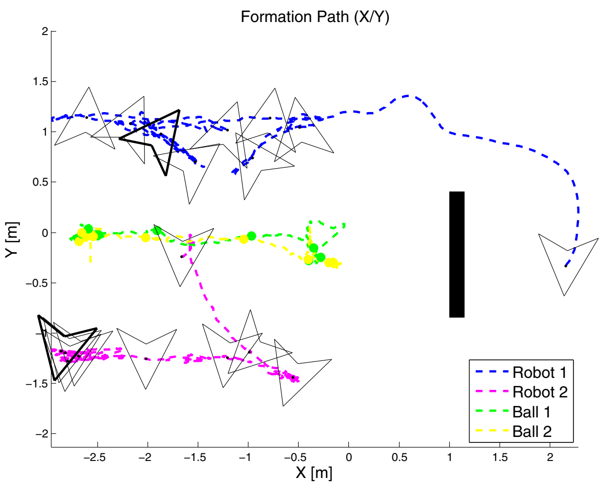


Fig. 5. Robots trajectories.

A graph with the distance between the robot and the ball and the minimization of the merged covariance's determinant can be seen in Fig. 7. As the minimization of the covariance is cooperative, robot 1 moves itself into another pose allowing robot 2 to place itself in a such a fashion that the convergence is achieved. It can also be seen through Fig. 5 that in the real experiment the convergence of both robots towards the target was accomplished.

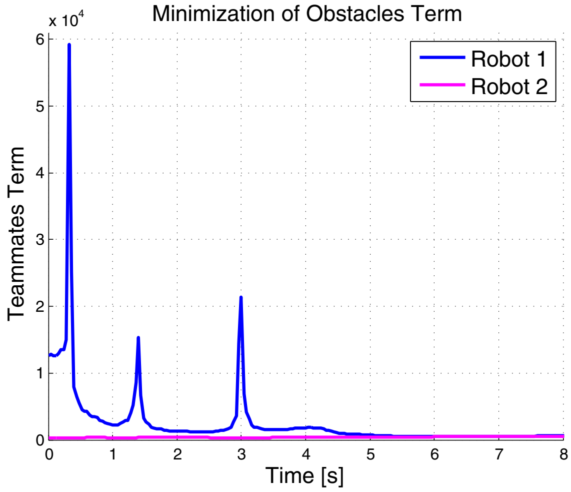
6. CONCLUSION

This paper presents a nonlinear model predictive formation controller for multi-robots systems. Artificial potential fields are included as terms of the cost function, in order to avoid obstacles and teammates collisions.

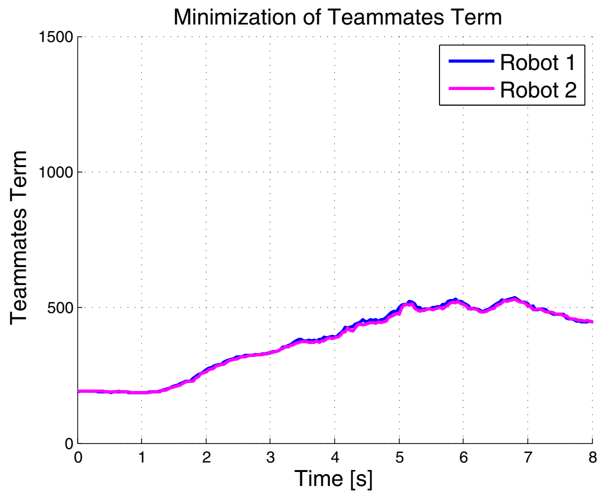
The controllers were embedded in omnidirectional mobile robots and experiments considering vision obstruction and static obstacle between the robots and the target were performed. This problem lies in the fact that the target is initially absent for one robot and the formation of a multi-robot system must converge to this target in the environment.

The NMPFCs are implemented in a distributed fashion, and the coupling occurs when the teammates' states are used in the cost function of each robot's controller to penalize the geometry or the deviation from the desired objective. The distributive configuration was created using wireless communication, where each robot received data from the other robots and processed its own task in the formation without the need of any kind of supervisor.

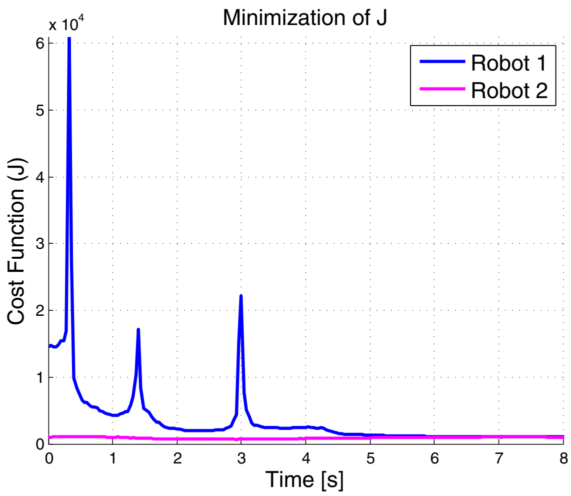
The main advantage of this approach is to consider in the same minimization problem both controller and obstacle/mate avoidance problem. This approach excludes the need of a path planner in the active target tracking problem.



(a) Obstacles Term.



(b) Teammates Term.



(c) All terms.

Fig. 6. Terms of the cost function.

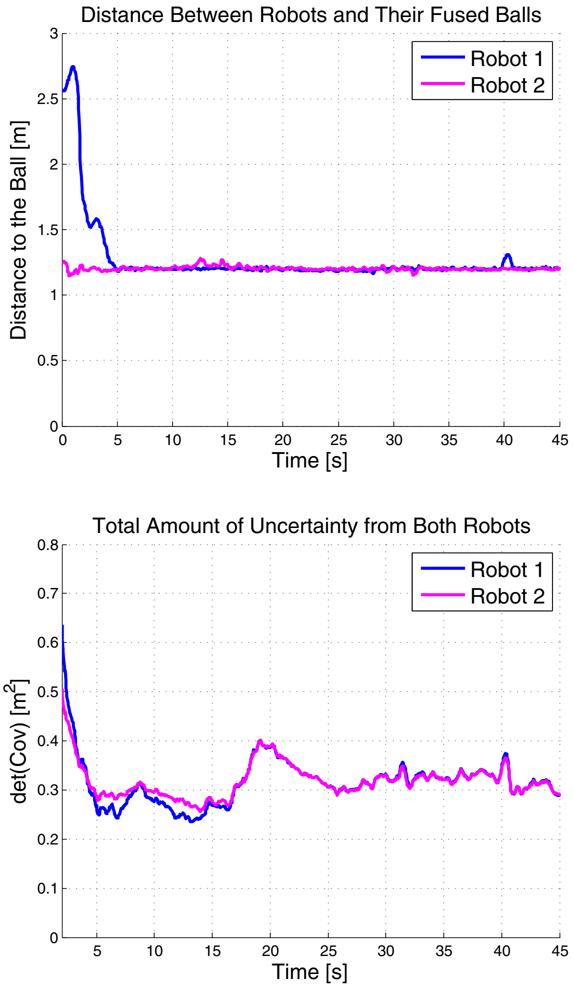


Fig. 7. Distance between Robot and Determinant of $\Sigma^{\perp}_{\text{Merged}}$.

The results demonstrated the efficiency of this approach in active target tracking with obstacle avoidance and vision obstruction in experiments with real robots. Future works includes cases of singularities, where algorithms of path planner can be used in order to exit entrapment situations.

ACKNOWLEDGEMENTS

The authors would like to acknowledge the financial support of the FAPESB, CNPq and CAPES Foundation - Proc: 1831-13-5.

REFERENCES

Ahmad, A. and Lima, P. (2011). Multi-Robot Cooperative Object Tracking Based on Particle Filters. In *5th European Conference on Mobile Robots, Örebro, Sweden*, 1–6.

Ahmad, A., Nascimento, T., Conceicao, A.G., Moreira, A.P., and Lima, P. (2013). Perception-driven multi-robot formation control. In *Robotics and Automation (ICRA), 2013 IEEE International Conference on*, 1851–1856. doi:10.1109/ICRA.2013.6630821.

Alejo, D., Conde, R., Cobano, J.A., and Ollero, A. (2009). Multi-UAV collision avoidance with separation assurance under uncertainties. In *2009 IEEE International Conference on Mechatronics, Malaga, Spain*, 1–6.

Bemporad, A. and Rocchi, C. (2011). Decentralized linear time-varying model predictive control of a formation of unmanned aerial vehicles. In *50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC)*, 7488–7493.

Camacho, E.F. and Bordons, C. (2004). *Model Predictive Control*. Springer, London, England.

Conceicao, A., Moreira, A., and Costa, P. (2009). Practical approach of modeling and parameters estimation for omnidirectional mobile robots. *Mechatronics, IEEE/ASME Transactions on*, 14(3), 377–381. doi:10.1109/TMECH.2009.2013615.

Hernandez-Martinez, E.G. and Bricaire, E.A. (2012). Non-collision conditions in multi-agent virtual leader-based formation control. *Int J Adv Robot Syst*, 9(100), 1–10.

Khantanapoka, K. and Chinnasarn, K. (2009). Pathfinding of 2D & 3D game real-time strategy with depth direction A* algorithm for multi-layer. In *2009 Eighth International Symposium on Natural Language Processing, Seattle, WA - USA*, 1249–1254.

Latombe, J.C. (1991). *Robot Motion Planning*. Kluwer Academic Publishers.

Maestre, J.M., de la Pena, D.M., and Camacho, E.F. (2011). Distributed model predictive control based on a cooperative game. *Optimal Control Applications and Methods*, 32(2), 153–176.

Nascimento, T.P., Moreira, A.P., Conceio, A.G.S., and Bonarini, A. (2013a). Intelligent state changing applied to multi-robot systems. *Robotics and Autonomous Systems*, 61(2), 115 – 124. doi:http://dx.doi.org/10.1016/j.robot.2012.10.011.

Nascimento, T.P., Moreira, A.P., and Conceicao, A.G.S. (2013b). Multi-robot nonlinear model predictive formation control: Moving target and target absence. *Robotics and Autonomous Systems*, 61(12), 1502 – 1515. doi: http://dx.doi.org/10.1016/j.robot.2013.07.005.

Nascimento, T.P., Conceição, A.G.S., Costa, P.G., Costa, P., and Moreira, A.P.G.M. (2012). A set of novel modifications to improve algorithms from the A* family applied in mobile robotics. *Journal of the Brazilian Computer Society*, 18(4), 167–179.

Oliveira, L., Almeida, L., and Santos, F. (2012). A Loose Synchronisation Protocol for Managing RF Ranging in Mobile Ad-Hoc Networks. In *RoboCup 2011: Robot Soccer World Cup XV, Lecture Notes in Computer Science, Springer Berlin Heidelberg, Istanbul, Turkey*, 574–585.

Pathak, K. and Agrawal, S.K. (2005). An Integrated Path-Planning and Control Approach for Nonholonomic Unicycles Using Switched Local Potentials. *IEEE Transactions on Robotics*, 21(6), 1201–1208.

Ribeiro, T., Ferrari, R., Santos, J., and Conceicao, A. (2013). Formation control of mobile robots using decentralized nonlinear model predictive control. In *Advanced Intelligent Mechatronics (AIM), 2013 IEEE/ASME International Conference on*, 32–37. doi:10.1109/AIM.2013.6584064.

Yang, S.X. (2002). Real-time torque control of nonholonomic mobile robots with obstacle avoidance. In *Proceedings of the IEEE Internatinal Symposium on Intelligent Control, Vancouver, Canada*, 81–86.