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Multi-Robot nonlinear model predictive formation control: the obstacle avoidance problem

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SUMMARY
This paper discusses about a proposed solution to the obstacle avoidance problem in multi-robot systems when applied to active target tracking. It is explained how a nonlinear model predictive formation control (NMPFC) previously proposed solves this problem of fixed and moving obstacle avoidance. First, an approach is presented which uses potential functions as terms of the NMPFC. These terms penalize the proximity with mates and obstacles. A strategy to avoid singularity problems with the potential functions using a modified A* path planning algorithm was then introduced. Results with simulations and experiments with real robots are presented and discussed demonstrating the efficiency of the proposed approach.

KEYWORDS: Obstacle avoidance; Nonlinear model predictive control; Mobile robots.

1. Introduction
The obstacle avoidance problem forms a well known area of research in mobile robotics. It is a study that involves a wide range of subjects which encompasses from a single robot movement to a group of mobile robots moving in a specific formation. Issues like static or mobile obstacle avoidance in single or multiple robots' motion are the main study cases in path planning.

Although many obstacle avoidance techniques rose over the years in mobile robotics,[7,22,26,30] this obstacle avoidance issue is still poorly researched in formation control problems with leader-following approaches using model predictive control theory.[5,16–18,28,31] In the leader-following approach of formation control several studies considering obstacles have been made such as[6,9,10,12] and.[29]

Regarding the use of MPC theory, the authors in ref. [8] present a model predictive control (MPC) approach for multi-vehicle formation. They take into account localization uncertainty, collision avoidance and velocity limitation with reduced computational burden. The paper constructs a formation control law using feedback linearization with MPC in order to reduce the optimal control problem to amixed-integer quadratic programming problem for a group of unicycles and also constructs a new branch-and-bound based algorithm for collision avoidance problems.

The authors in ref. [15] presented a decentralized model predictive control to solve the problem of formation stabilization and tracking for a group of nonholonomic mobile robots. In the stabilization problem, the robots started from an arbitrary initial condition and reach a certain formation i.e. desired relative position and orientation. In the tracking problem under consideration, a desired trajectory was given to the leader of the formation. The followers kept a specified distance and orientation while following their leaders to keep a certain formation. Virtual force method was also used to avoid

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obstacles. All the agents in the formation avoid obstacles by producing a local virtual force with respect to their distance from the obstacle.

This paper differs from the above mentioned papers in the sense that here it is used a nonlinear model predictive controller (NMPC). This theory applied to formation control discards the need to linearize the nonlinear system in order to control it. Another difference is that, except in the work of,[15] most formation control systems are implemented in a centralized fashion. In our case, the NMPFC is implemented in a distributed fashion using ad-hoc communication.

It is notable that all previous cited works, even in the case when formation control uses NMPC theory,[13] presented experiments that puts the formation to follow a pre-set trajectory which differs from this paper's case of study. In this paper, the active target tracking problem (ATT) is considered. In the active target tracking problem, there is no reference trajectory.[19,20,32,33] The convergence is performed based on an observable target (here stated as a soccer ball).

The idea to solve a formation control problem was first addressed in our previous work[23] where it was implemented a nonlinear model predictive controller (NMPC). The formation was formed by a group of omnidirectional mobile soccer robots,[24] usually participants of RoboCup.[1] The authors in ref. [23] presented a solution where the cost function had still many usual problems raised by the nonlinearities in the NMPC cost function such as convergence robustness, no obstacle avoidance solution, limited amount of mates in formation, and did not considered the observation model in the cost function, which in turn could not be applied to solve the active target tracking problem. Finally, the work in ref. [23] was not implemented in a distributed fashion. Considering the active target tracking problem in formation control, a perception driven formation controller using NMPC theory was conceived,[21] where keeping the formation was analyzed during a moving target and during the target absence, and where the formation robustness was proven. This controller was called nonlinear model predictive formation controller (NMPFC) and its cost function was composed by several terms that penalizes different behaviors. One of these behaviors and probably the most important one was the target's observation penalization term which penalized the total amount of uncertainty in the group's target perception. The target's observation penalization was analyzed in another paper by the same authors.[3] In this study, the nonlinear model predictive formation controller (NMPFC) is applied to an highly dynamic environment to demonstrate the use of the NMPFC in converging a group of mobile robots towards a desired target, while avoiding teammates, static or moving obstacles and minimizing the total amount of uncertainty in the target's perception of the group. This approach proposes the use of potential functions as terms of the NMPFC cost function where it is commuted with an A* path planner only in singularity cases by a switching behavior. In the next section the NMPFC proposed is briefly explained. In Section 3 the potential field approach used in the cost function of the NMPFC is explained. In Section 4 the simulated results and the results with real robots experiments are presented. Finally, the conclusion is exhibited in the last section.

2. Nonlinear Model Predictive Formation Control Architecture

The most common implementation type of a nonlinear model predictive controller (NMPC) is centralized. The centralization holds all the system's knowledge computing all the control inputs. In complex systems where the environment has high dynamics, using a non-convex optimization scheme may be a solution not feasible in most applications.

The use of communication networks and in turn distributed control schemes, became more common being applied to solve problems of centralization allowing the usage of a NMPC in such applications (e.g. mobile robotics). The NMPC used in such applications is here called NMPFC, or nonlinear model predictive formation controller, where the agents share information in order to improve closed-loop performance, robustness and fault-tolerance.[14]

The NMPFC can be divided into two sub-blocks. The first sub-bloc, here called **Optimizer**, uses an online 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. Substantially different to other adaptive techniques, the effect of the RPROP adaptation process is not blurred by the unforeseeable influence of the size of the derivative. In fact, it only depends on the temporal behavior of its sign. This leads to an efficient and transparent adaptation process. More

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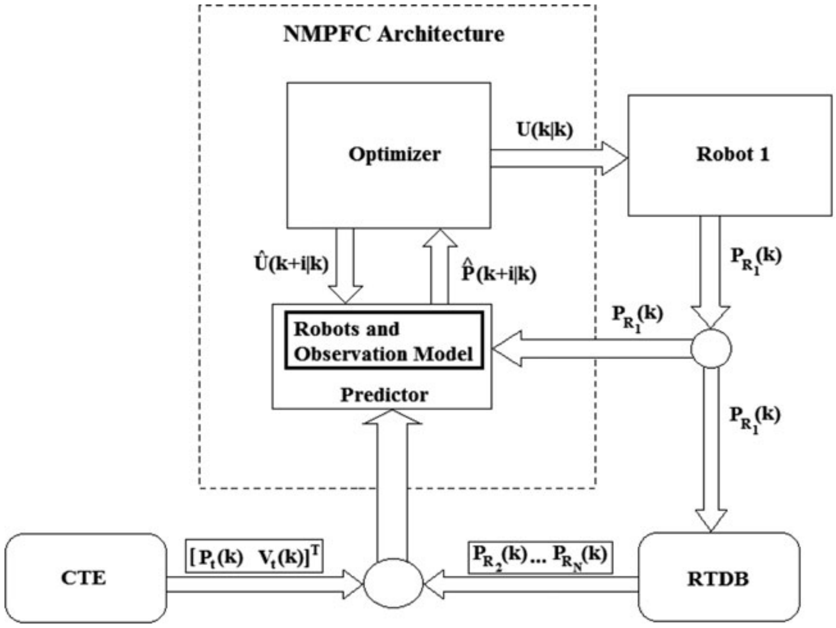

Fig. 1. Controller diagram.

details on the RPROP can be found in ref. [27]. The second sub-block, the **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. 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 (as demonstrated in Fig. 1). The predictor also emulates the evolution of the target's merged state covariance matrix.

In this distributed controller scheme, robot 1 sends its pose ($P_{R_1}(k) = [\,x_{R_1}(k) \quad y_{R_1}(k) \quad \theta_{R_1}(k)\,]^T$) to the controller's **Predictor** and to a real time data base (RTDB)[25] communication application to be shared with the other robots in formation through wireless communication, at each instant k. This information is acquired through localization and vision systems inside the block Robot 1. Then, the RTDB sends back to the controller's **Predictor** the pose of each robot in formation ($[P_{R_2}(k)..P_{R_N}(k)]$). A cooperative target estimator (CTE) communicates locally to the NMPFC the information on the fused position of the target t in the world frame ($P_t(k) = [\,x_t(k) \quad y_t(k)\,]^T$) and the fused target velocity t in the world frame ($V_t(k) = [\,v_{x_t}(k) \quad v_{y_t}(k)\,]^T$).[2] Finally, the controller's **Optimizer** sub-block provides the control input $\hat{U}(k+i|k)$, in a limited control horizon, to the predictor sub-block, which then predicts the formation state evolution $\hat{P}(k+i|k)$ for N_p steps (prediction horizons), and provides a cost value to the optimizer in accordance with $\hat{U}(k+i|k)$. As it can be seen in Fig. 1, $U(k|k) = U(k) = [\,v_{ref}(k) \quad vn_{ref}(k) \quad w_{ref}(k)\,]^T$ is the output control signal in the first prediction step. Furthermore, it is important to notice that $\hat{U}(k+i|k)$ with $i = 0..N_p - 1$ is the output control signal from the optimizer sent to the predictor in each prediction step and $\hat{P}(k+i|k)$ with $i = 1..N_p$ is the response of the predictor block to each $\hat{U}(k+i|k)$, sending the control output in the first step $U(k)$ to the robot. After processing the control calculations, the NMPFC sends the desired control output back to the robot (controller's reference velocities).

2.1. The cost function

The objective of this paper is to discuss about the obstacle avoidance problem considered when implementing a nonlinear model predictive formation controller (NMPFC) for a multi-robot systems formation control applied to the active target tracking problem. Here, the obstacles are detected using an inboard camera. Our solution to this problem was first addressed in our previous work[23] where it was implemented a nonlinear model predictive controller (NMPC) in formation control. The cost function used us in ref. [23] can be seen in the

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Eq. (1).

$$
\begin{aligned}
J(N_1, N_p, N_c) = & \sum_{i=N_1}^{N_p} \lambda_1 \left(D_{val} - ||P_{\mathrm{t}}^{\mathrm{R}_n}(k+i)|| \right)^2 \\
& + \sum_{i=N_1}^{N_p} \lambda_2 \left(\hat{P}_{\mathrm{t}}^{\mathrm{R}_n}(k+i) \cdot \hat{v}_{ball}(i) \right)^2 \\
& + \sum_{i=N_1}^{N_p} \lambda_3 \left(\left(\frac{1}{||P_{\mathrm{R}_n}^{\mathrm{R}_{m1}}(k+i)|| - D_M} \right)^2 \right. \\
& \left. + \left(\frac{1}{||P_{\mathrm{R}_n}^{\mathrm{R}_{m2}}(k+i)|| - D_M} \right)^2 \right) \\
& \sum_{i=N_1}^{N_p} \lambda_4 \left(diffAngle \left(\theta_{\mathrm{R}_n}(k), \theta_{\mathrm{t}}^{\mathrm{R}_n}(k+i) \right) \right)^2 \\
& + \sum_{i=1}^{N_c} \lambda_5 (\Delta U(k+i-1))^2,
\end{aligned}
\tag{1}
$$

The cost function of a NMPC (here NMPFC) represents the cost to be minimized by the predictive controller. It is typically associated with the changing dynamic of the system (formation geometry) over time. Therefore, it reduces the uncertainty on the target localization (a soccer ball) and velocity estimates, while keeping the robots apart and assigning costs to the robots motion (e.g., to get closer to a ball, typically to reduce the uncertainty of its position estimate). The desired formation for the robots to be around the ball in a way to better estimate the ball'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 work described in ref. [21] presented our new cost function that represents all the above requirements. This novel cost function, embedded in all robots, is as follows:

$$
\begin{aligned}
J(N_1, N_p, N_c) = & \sum_{i=N_1}^{N_p} \lambda_a \times |det(\Sigma_{\mathrm{Merged}}^{\perp}(k+i))| \\
& + \sum_{i=N_1}^{N_p} \lambda_1 \times |(D_{val} - ||P_{\mathrm{t}}^{\mathrm{R}_n}(k+i)||)| \\
& + \sum_{i=N_1}^{N_p} \lambda_2 \times |\delta(\theta_{\mathrm{R}_n}(k), \quad \theta_{\mathrm{t}}^{\mathrm{R}_n}(k+i))| \\
& + \sum_{i=N_1}^{N_p} \sum_{j=1}^{NM} \lambda_3 \times \max \left(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{R}_j}(k+i)||}{D_M}, 0 \right)
\end{aligned}
\tag{2}
$$

$$+\sum_{i=N_1}^{N_p}\sum_{l=1}^{NO}\lambda_4 \times \max\left(1-\frac{||P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)||}{D_O},0\right)$$
$$+\sum_{i=1}^{N_c}\lambda_5 \times |\Delta U(k+i-1)|$$

where N_1, N_p are the predicted horizon limits in discrete time. N_c is the control horizon. NM and NO are the number of teammates and the number of obstacles, respectively. λ_a, λ_1, λ_2, λ_3, λ_4 and λ_5 are the weights for each component of the cost function. $\Sigma_{\mathrm{Merged}}^{\perp}$ is the formation team's merged target observation covariance matrix. Also, $P_{\mathrm{t}}^{\mathrm{R}_n}(k+i)$ is the distance between the robot n and the target t, $\hat{P}_{\mathrm{t}}^{\mathrm{R}_n}(k+i)$ is the vectorial distance between the robot and the target, $P_{\mathrm{R}_n}^{\mathrm{R}_{m1}}(k+i)$ is the distance between the robot and the mate m_1, $P_{\mathrm{R}_n}^{\mathrm{R}_{m2}}(k+i)$ is the distance between the robot and the mate m_2, $P_{\mathrm{R}_n}^{\mathrm{R}_j}(k+i)$ is the distance between the robot n and the teammate j, $P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)$ is the distance between the robot n and the obstacle l, the given value where small distances between the robot and its teammates are not penalized is D_M and D_O has the same purpose of D_M but regarding obstacles. D_{val} is the threshold distance between the robot and the ball. $\Delta U(k+i-1)$ 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.

3. Potential Field Approach in NMPFC

The NMPFC is inserted in the optimal control group. It means that this kind of controller uses an optimizer algorithm to find the best solution, or optimal control output. When considering such controllers in real time optimization many approaches are available. Nevertheless, the obstacle avoidance approach that most rapidly and easily fits into this kind of control is the artificial potential fields (APF) approach. In ref. [4], 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 Eq. (2). 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.[11] 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:

$$U_{rep}(q)=\begin{cases}\frac{1}{2}\eta\left(\frac{1}{\rho(q)}-\frac{1}{\rho_0}\right)^2 & \text{if} \quad \rho(q)\le\rho_0\\ 0 & \text{if} \quad \rho(q)>\rho_0\end{cases} \tag{3}$$

where η is a positive scaling factor, q is the position of a robot A in the workspace W, q' is the position of a robot A inside the obstacle region (CB), $\rho(q)$ denotes the distance from q to the obstacle region (CB), i.e.:

$$\rho(q)=\min_{q'\in CB}||q-q'|| \tag{4}$$

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.

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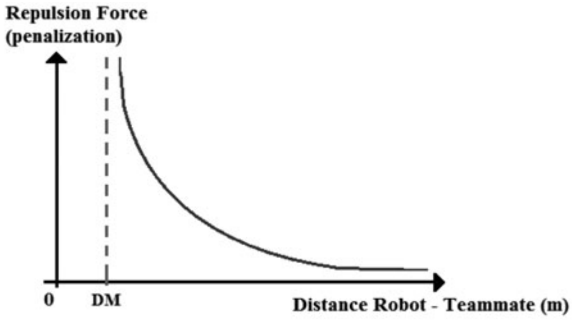

Fig. 2. Behavior of function in 5.

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.

3.1. *Mate avoidance function*

The first idea of a term in a NMPC that penalizes the approximation between robots in a formation was presented in our previous work.[23] In this work, the authors created a term in their nonlinear model predictive controller cost function such as in the Eq. (5).

$$\sum_{i=N_1}^{N_p} \lambda_3 \left(\left(\frac{1}{||P_{\mathrm{R}_n}^{\mathrm{R}_{m1}}(k+i)|| - D_M} \right)^2 \left(\frac{1}{||P_{\mathrm{R}_n}^{\mathrm{R}_{m2}}(k+i)|| - D_M} \right)^2 \right) \tag{5}$$

Where $||P_{\mathrm{R}_n}^{\mathrm{R}_{m1}}(k+i)||$ is the distance between robot R_n and the mate 1. This function has a nonlinear decreasing behavior as shown in Fig. 2.

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. The position of the teammates were shared through a normal access point network

A simple solution is proposed here to avoid these problems. Besides the change in network, where in this paper it was used the RTDB, the omnidirectional mobile soccer robots share their positions among the teammates. Therefore, all robots in formation receive through the RTDB the position of its mates besides sharing their own. The proposed term for mate avoidance can be seen in Eq. (6).

$$\sum_{i=N_1}^{N_p} \sum_{j=1}^{NM} \lambda_3 \times \max\left(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{R}_j}(k+i)||}{D_M}, 0\right) \tag{6}$$

Noticing that NM is the maximum number of mates, $||P_{\mathrm{R}_n}^{\mathrm{R}_j}(k+i)||$ 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 paper.

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.

3.2. Obstacle avoidance function

In the obstacle avoidance problem, if the position of the obstacles would be shared though RTDB this would jeopardize the communication of the formation. In this case, the obstacles' position are not shared and the obstacle avoidance is performed by each robot, and not by the formation. This allows the robots in formation to avoid the obstacles more rapidly. The final penalization of each term of the cost function stabilizes the formation maintaining even if for a while the formation had to be broken in order to avoid fast moving obstacles. Therefore, an obstacle avoidance function was created based on the idea of mates avoidance function and the potential field approach. The repulsion term proposed in this paper can be seen in Eq. (7).

$$\sum_{i=N_1}^{N_p} \sum_{l=1}^{NO} \lambda_4 \times \max\left(1 - \frac{||P_{\mathrm{R}_n}^{\mathrm{O}_l}(k+i)||}{D_O}, 0\right) \tag{7}$$

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 40 ms refreshment of sensory data. This assumption speeds up the calculations (which happens during 10 ms) in the prediction of the NMPFC by calculating only the robot-obstacle distance evolution in a simplified fashion. Nevertheless, the static obstacles have a major issue in potential fields approach: the local minima problem. The most common problem of APF lies in a robot being stuck in a local minima. It is the case that occurs when the total force acting on the agent is summed up to zero even though the robot has not reached its goal position yet. Figure 4 shows the local minima problem case.

In order to solve this problem, a switching approach was implemented inside a behavior (here called role). This specific behavior is the role *Formation*. In this approach, the NMPFC with the potential function term is substituted by a controller with a modified A* path planning algorithm[22] if the robots gets trapped in a local minima (if the path towards the target is obstructed and if there are obstacles in one of the robot's side). In most of this local minima problems, the robot encounters obstacles at least in two sides (for example in front of it and by one side making an L shape). In this case, it turns off the potential field term and turns on the A* algorithm. Once the robot is outside the entrapment region (there is no more obstruction between the robot and the target), the role *Formation* turns off the A* algorithm and turns back on the potential functions. The switching approach is implemented in the formation role as illustrated in Fig. 3. This switch is due to the fact that the potential functions have much less computational costs then using A* path planning and when the A* is executed it is necessary to stop processing some features of the controller in order to speed up the processing.

Finally, the same consideration that was made in the teammate avoidance function, had to be considered in the obstacle avoidance function by including 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.

4. Results

Several simulations were performed to validate the controller. Furthermore, some experiments with real robots were also performed in order to see the behavior of the group under communication, vision and localization problems. In total, they were 30 simulations of each case and 10 real robot

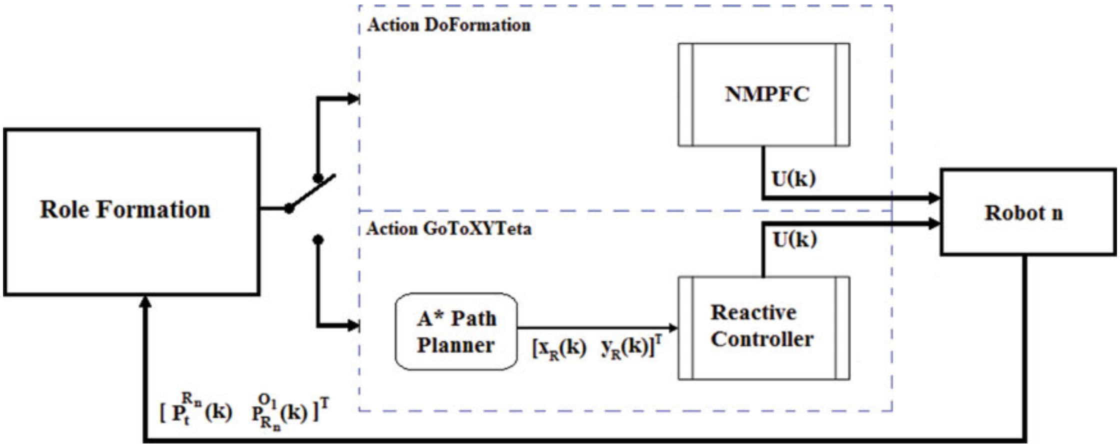

Fig. 3. Switching approach.

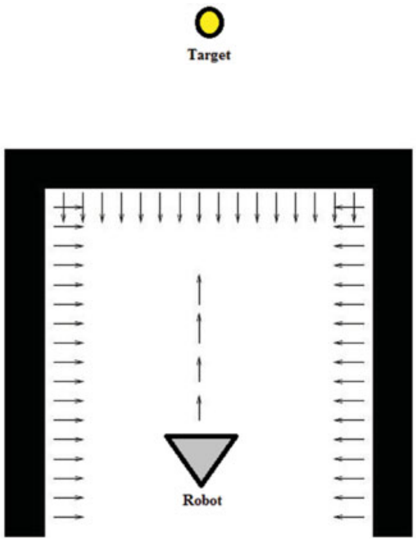

Fig. 4. Local minima problem case.

experiments of each case. For all results the same parameters were used. Nevertheless, some aspects must be noticed such as follows:

– Distance between Robot and Ball = 1.2 m;
– Velocity of the Robots in Formation = 1.5m/s in simulations and 0.7 m/s in real experiments;
– The parameters from the NMPFC optimizer (Resilient Propagation algorithm) were the same ones used in ref. [23] with a maximum of 20 interactions;
– The control horizon was $N_c = 2$ and the prediction limits were $N_1 = 1$ and $N_2 = 7$.

The final weight values found through exhaustive simulations and experiments can be seen in Table I.

4.1. Simulations

The simulation setup was done with two computers and the SimTwo simulator environment.[22] The static obstacles in the simulation were considered to be boxes with $0.75 \times 0.75 \times 0.5$ m (depth $\times$ width $\times$ height) in dimension. The moving obstacles are considered as self moving spheres in a semi-random path.

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Table I. Final weights for the cost function.

λ	Weights	Weights in critical situation
λ_a	505	50
λ_1	918	918
λ_2	297	297
λ_3	500	2000
λ_4	500	2000
λ_5	5.00	5.00

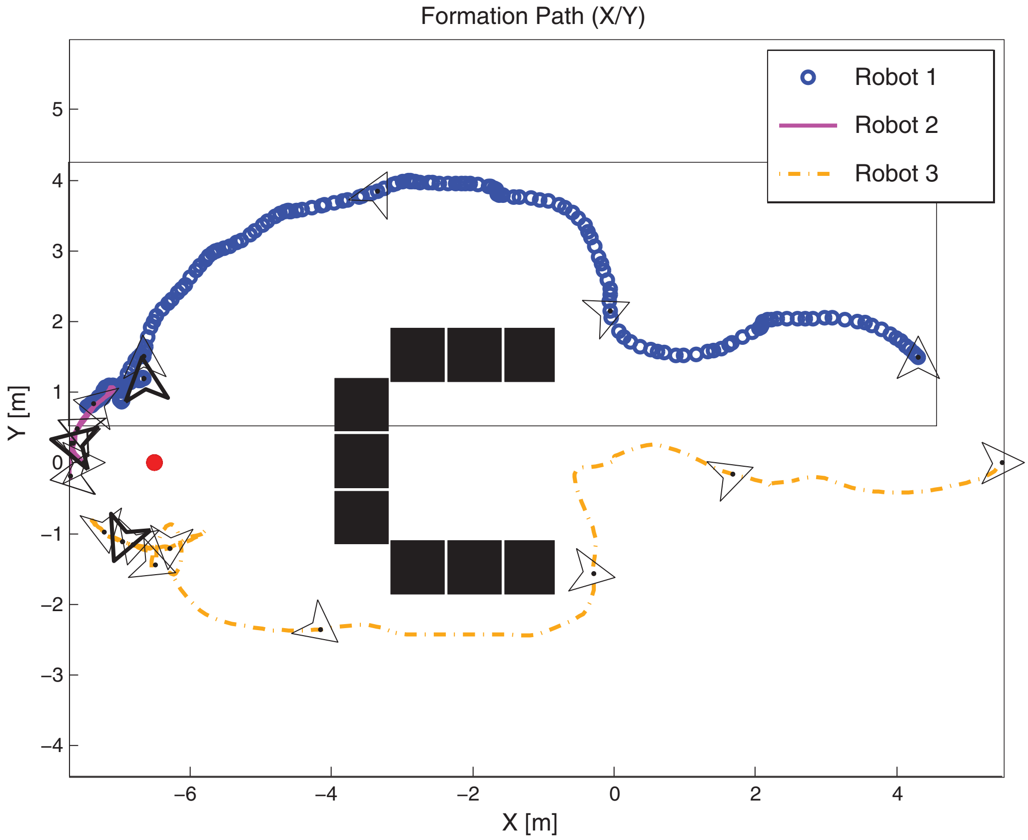

Fig. 5. Simulation 1: plot XY.

4.1.1. Simulation 1. The first simulation addresses the entrapment problem in obstacle avoidance where the formation has to avoid an U shape obstacle during the convergence towards the target. The objective here is to converge the robots towards the ball departing from the coordinates (4.3,1.5), (−7.5,0), (5.5,0) and (−6.5,0) for the robots 1, 2, 3 and target, respectively. The obstacles' walls are made by nine blocks in the coordinates (−2.8,1.5), (−2,1.5), (−1.2,1.5), (−2.8,−1.5), (−2,−1.5), (−1.2,−1.5), (−3.6,0.8), (−3.6,0) and (−3.6,−0.8). In this case, robot 2 is near the ball sending information to the other robots of where the target is located. Therefore, the NMPFC acts by attracting the robots and unavoidably puts the robots in a local minima as the potential function would behave. This was demonstrated in the path of robot 3 in Fig. 5. However, the modified A* path planner starts instantly when the robots enter this situation (at coordinates (−0.5,0)) and puts the robots outside the U shape obstacle.

While one of the robots (robot 3) detect the singularity situation and turns on the modified A* to leave the entrapment situation, the other robot (robot 3) succeeds avoiding it without the modified

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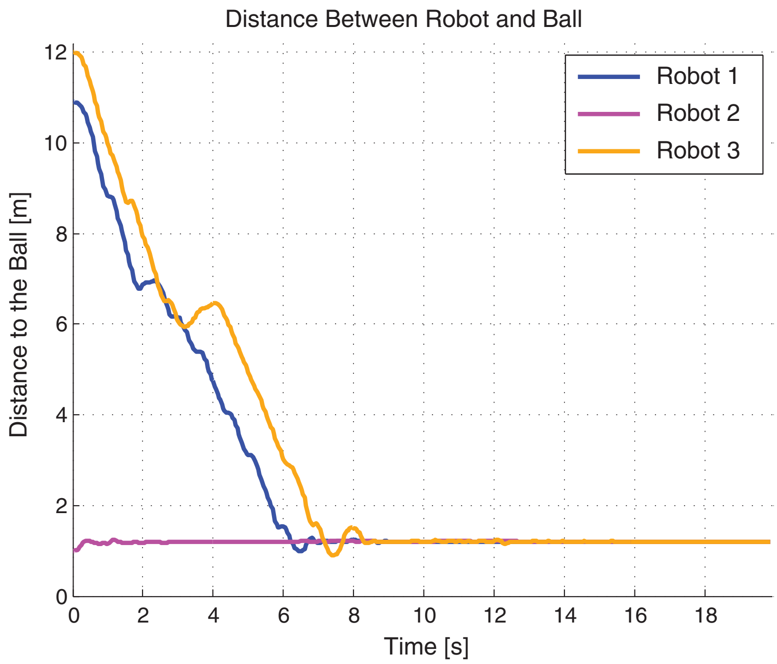

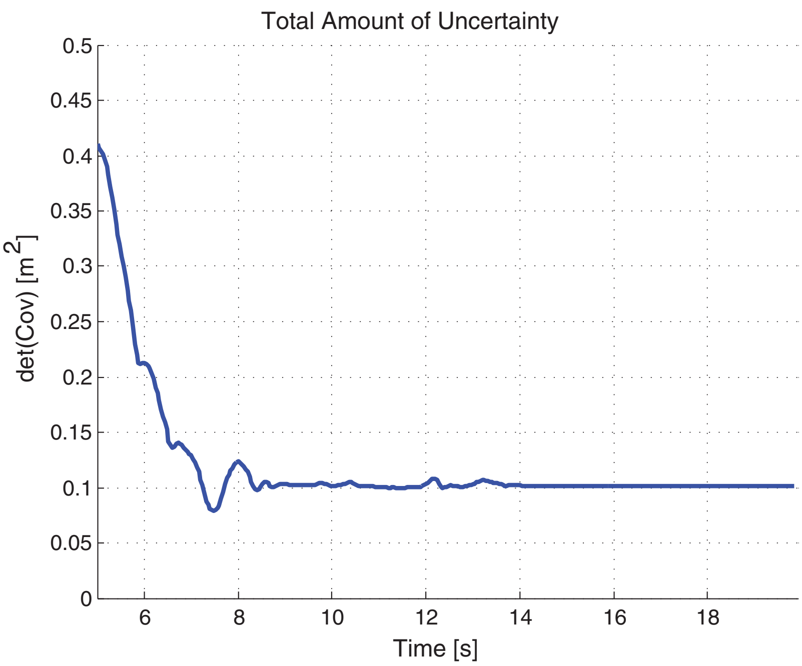

Fig. 6. Simulation 1: distance between robot and determinant of $\Sigma^{\perp}_{\text{Merged}}$.

A*. Note here that the covariance only starts at approximately 5 s when all robots are seeing the ball. A graph with the distance between the robot and the ball as well as the minimization of the merged covariance's determinant can be seen in Fig. 6. Finally, the robots' final position is highlighted in the figure (as well as the figures from the other simulations and experiments).

4.1.2. Simulation 2. In this simulation, the used field has 8×10 m of size. For the simulations in the unstructured environment the movement of the obstacles is set to be half random. That's because those movements are set by a simple algorithmic procedure in SimTwo. As it can be seen in the *Set*

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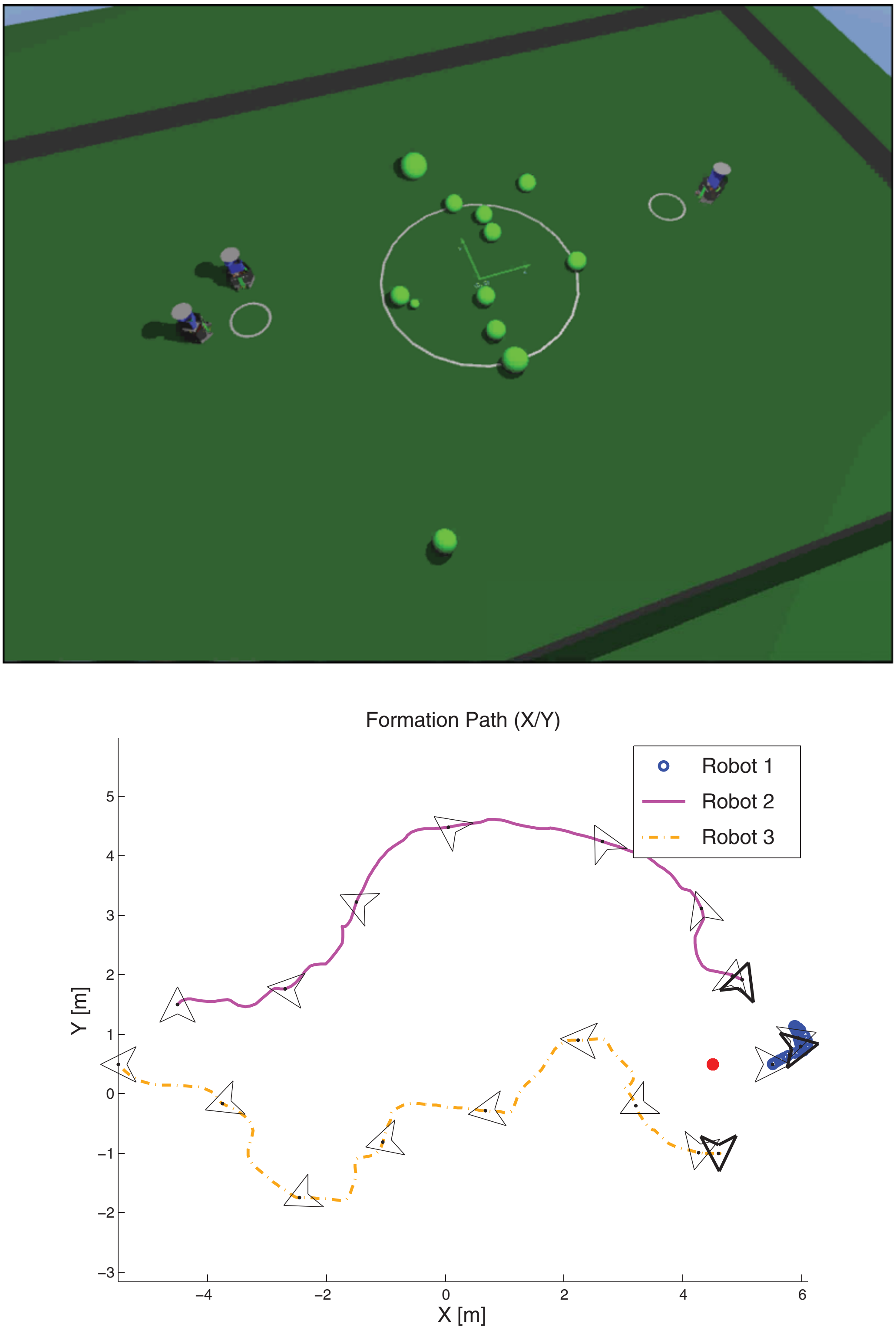

Fig. 7. Simulation 2 - environment and Plot XY.

Sphere Speed Algorithm, this uploads the values from each sphere and sets a force upon each one, making the movements. With a constant velocity for all the spheres, the movements of each one is practically always the same, except if the robot hits one or more sphere or if the spheres hit each other.

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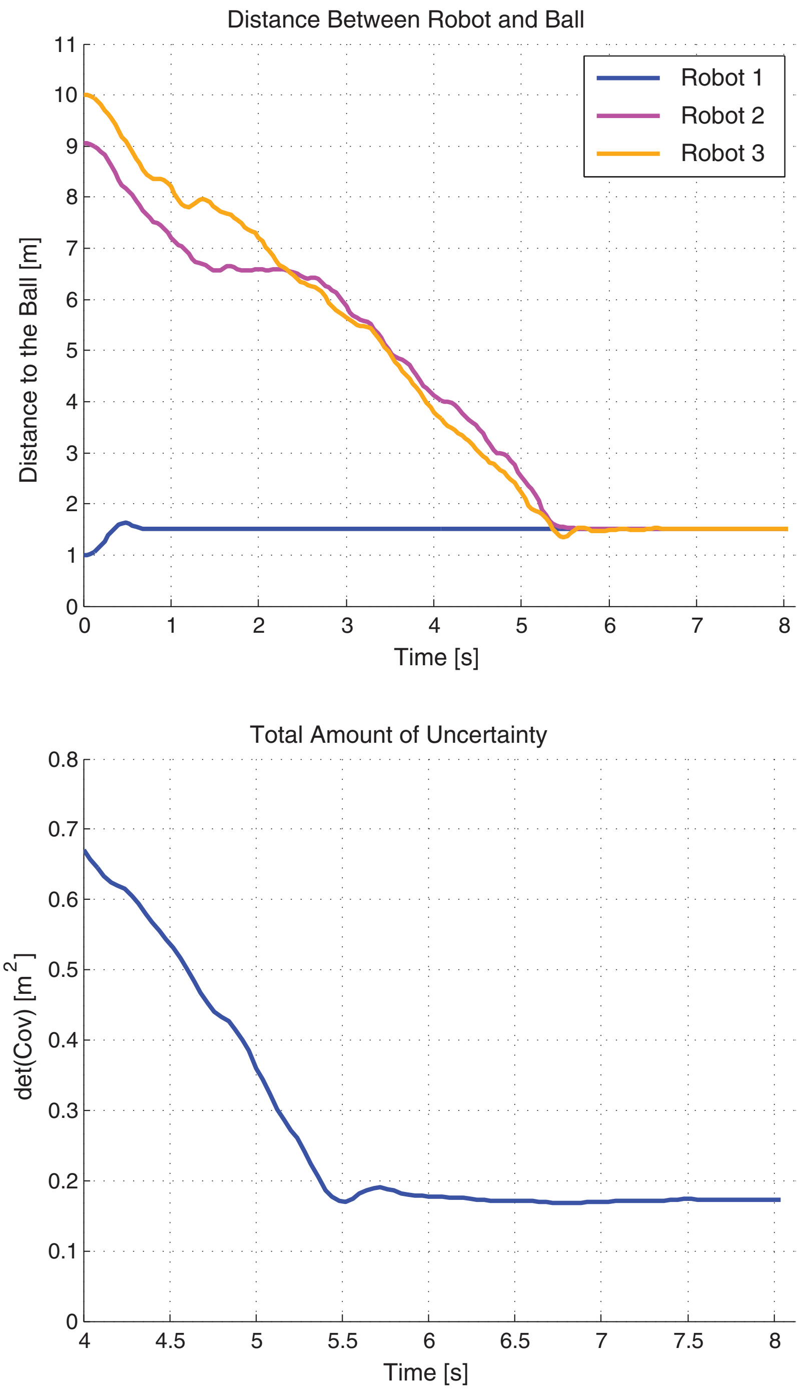

Fig. 8. Simulation 2 - distance between robot and ball and determinant of $\Sigma^{\perp}_{\text{Merged}}$.

In the algorithm, $NexPosition_x$ and $NexPosition_y$ are the next position of the ith-sphere, $Initial_x$ and $Initial_y$ are the initial position of the ith-sphere in the simulation, $Position_x$ and $Position_y$ are the current position of the ith-sphere, Radius is the radius of the ith-sphere, Speed is the velocity modulus of the ith-sphere, t is the increasing time during simulation and δ is the orientation of the ith-sphere's movement. Finally, V_x and V_y are the new ith-sphere's velocities.

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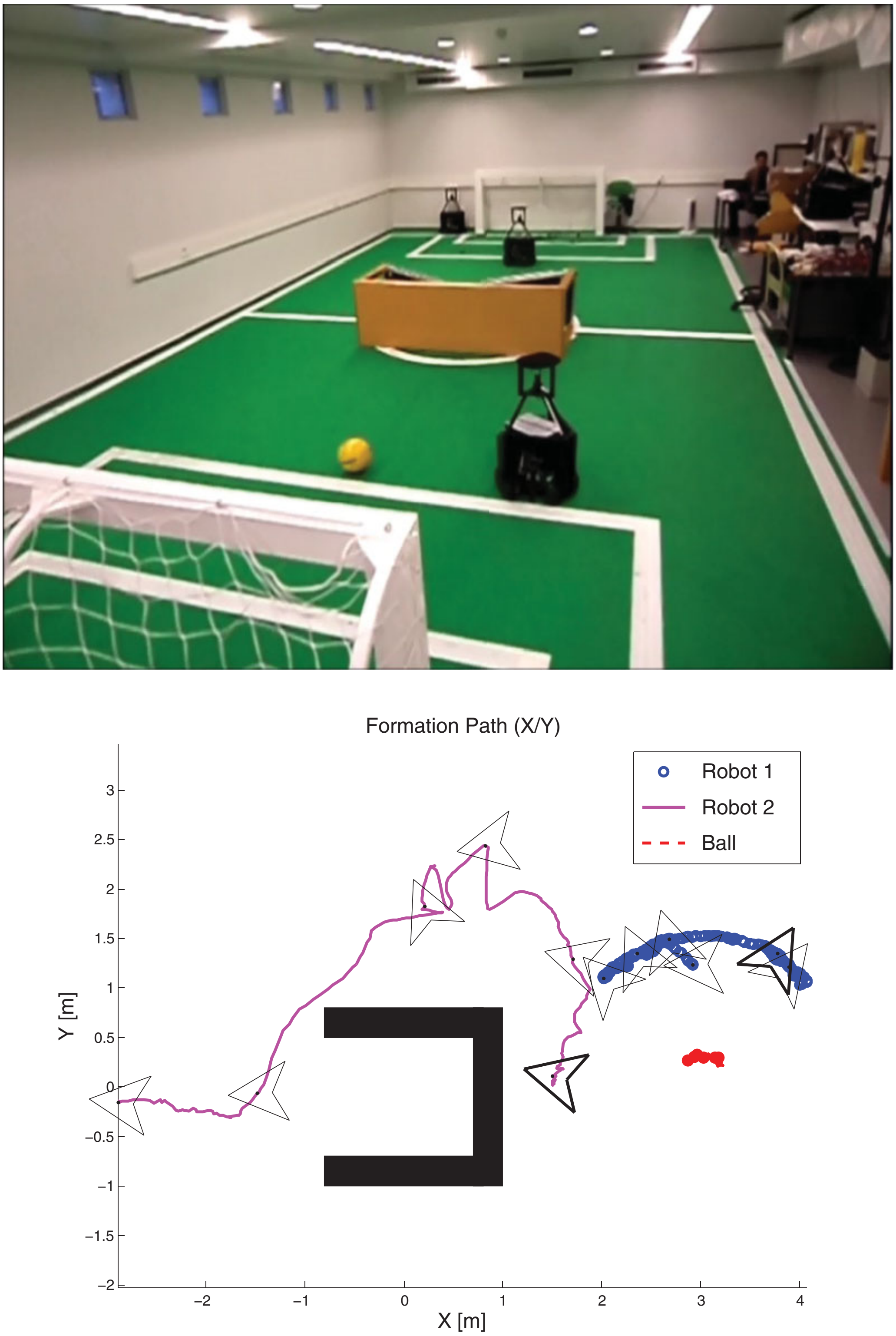

Fig. 9. Real experiment 1 - environment and plot XY.

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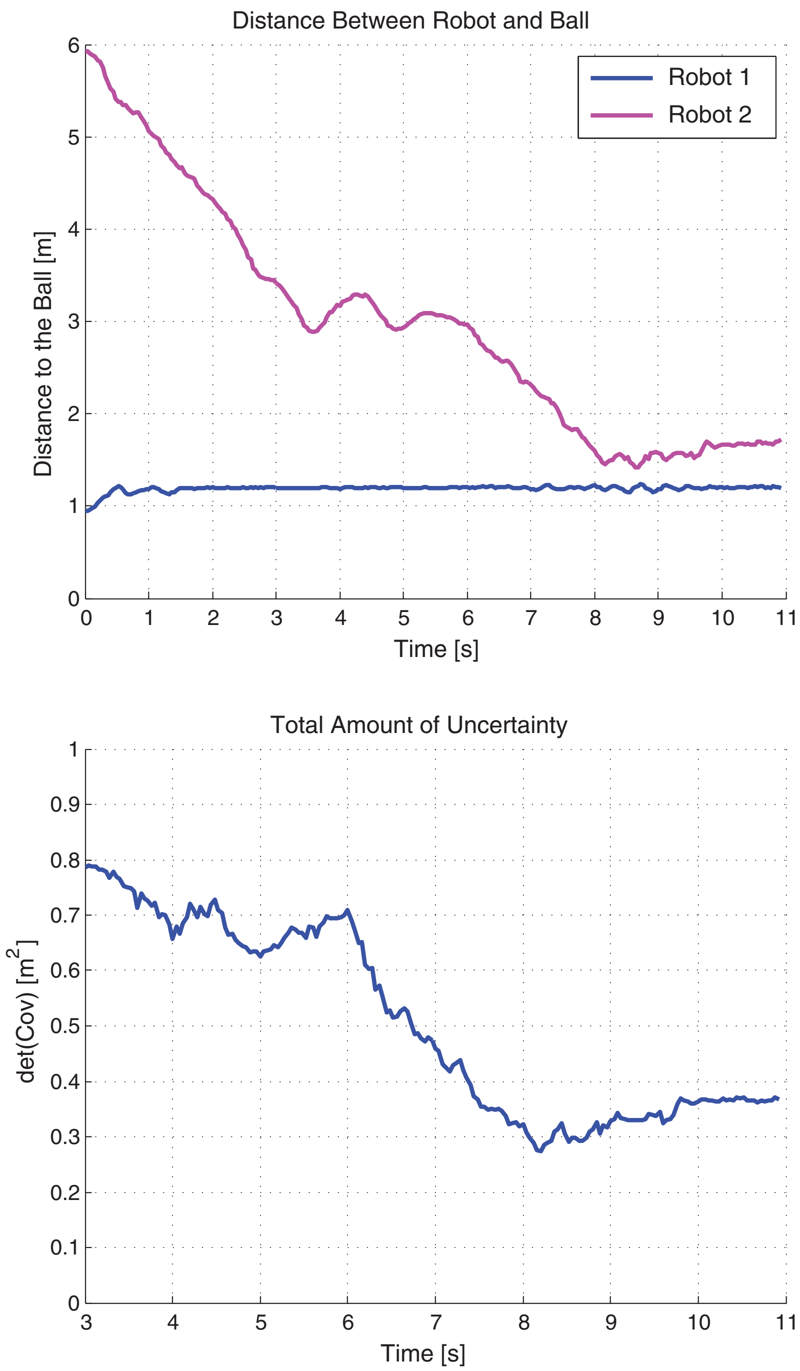

Fig. 10. Real experiment 1 - distance between robot and determinant of $\Sigma^{\perp}_{\text{Merged}}$.

Algorithm Set Sphere Speed

1: **If** $\exists$ Sphere **then**
2: $NexPosition_x = Initial_x + \text{Radius}\cdot\cos(\text{Speed}\cdot(\text{t}+\delta))$
3: $NexPosition_y = Initial_y + \text{Radius}\cdot\sin(\text{Speed}\cdot(\text{t}+\delta))$
4: **Set** Force of ith-Sphere with
5: $V_x = 100*(NexPosition_x - Position_x)$
6: $V_y = 100*(NexPosition_y - Position_y)$
7: $V_z = 0$
8: **end**
9: **end**

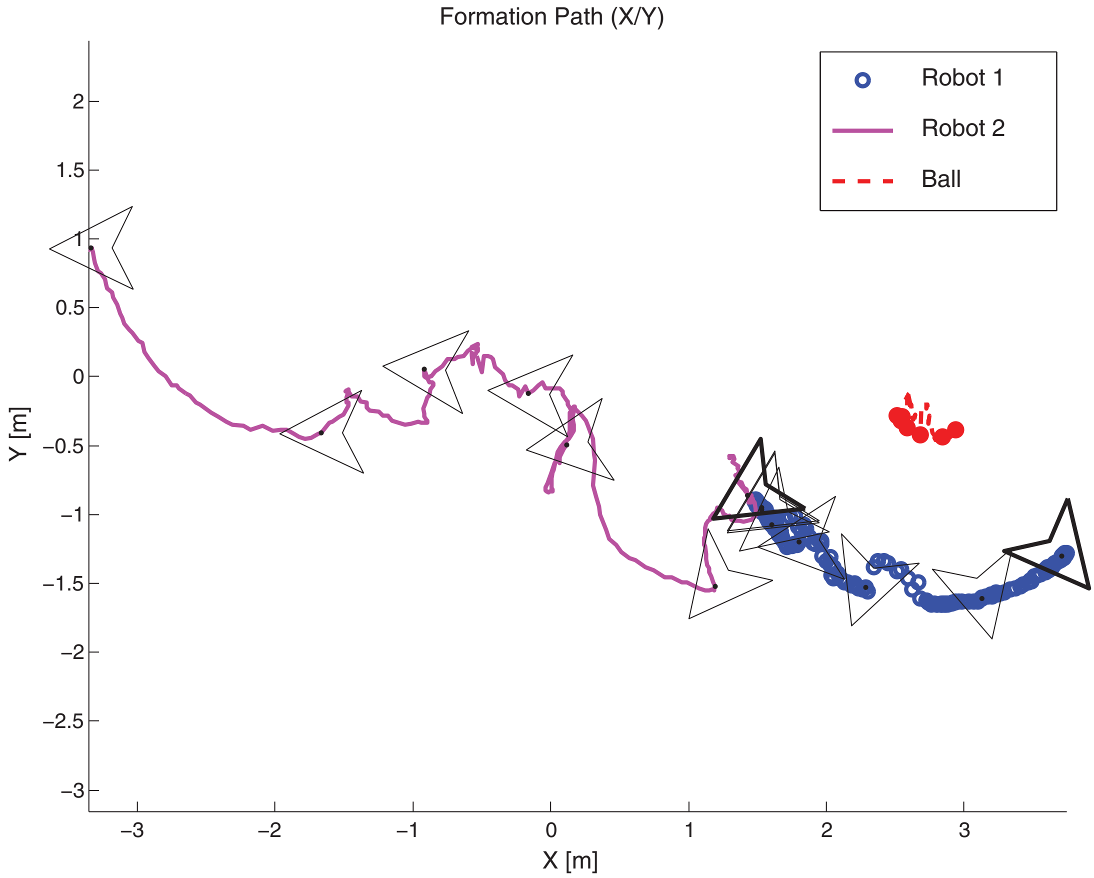

Fig. 11. Real experiment 2 - plot XY

This second simulation demonstrates the algorithm's behavior in a crowded environment. The objective is once more to converge the formation towards the ball, here represented as a circle. The robot leader is near the ball and it passes the target's coordinates to the other robots. The simulation environment is as presented in Fig. 7 with the path made by the robots in a XY plot. Here no collision happened between the robots and the twelve mobile obstacles and the robots converged towards the target successfully.

A graph with the distance between the robot and the ball as well as the minimization of the merged covariance's determinant starting at 4s (when all robots see the ball) can be seen in Fig. 8. The video **Simulation2** shows the robots' movement as presented in the plot XY.

4.2. Experiment with real robots

A setup, to perform experiments with real robots, 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. 1. Videos from all experiments are attached to this paper to aid in the analysis of the robots' behavior during the tests.

4.2.1. Real experiment 1. This experiment addresses the entrapment problem in obstacle avoidance where the robot has to avoid an U shape obstacle by changing the formation in order to avoid the obstacle. Similarly to simulation 1, the leader robot (robot 1) is near the ball, sending the information to the other robot (robot 2) of where the target is located. Therefore, the objective here is to converge to the ball departing from the coordinates (3,1.2), (−3,−0.2) and (3,0) for the robots 1, 2 and target, respectively. The NMPFC attracts the robot and unavoidably puts the robots in a local minima just as the potential function would behave. However, the A* path planner rapidly starts when the robots enter this situation and places the robots outside the U shape obstacle. The obstacles' walls and the

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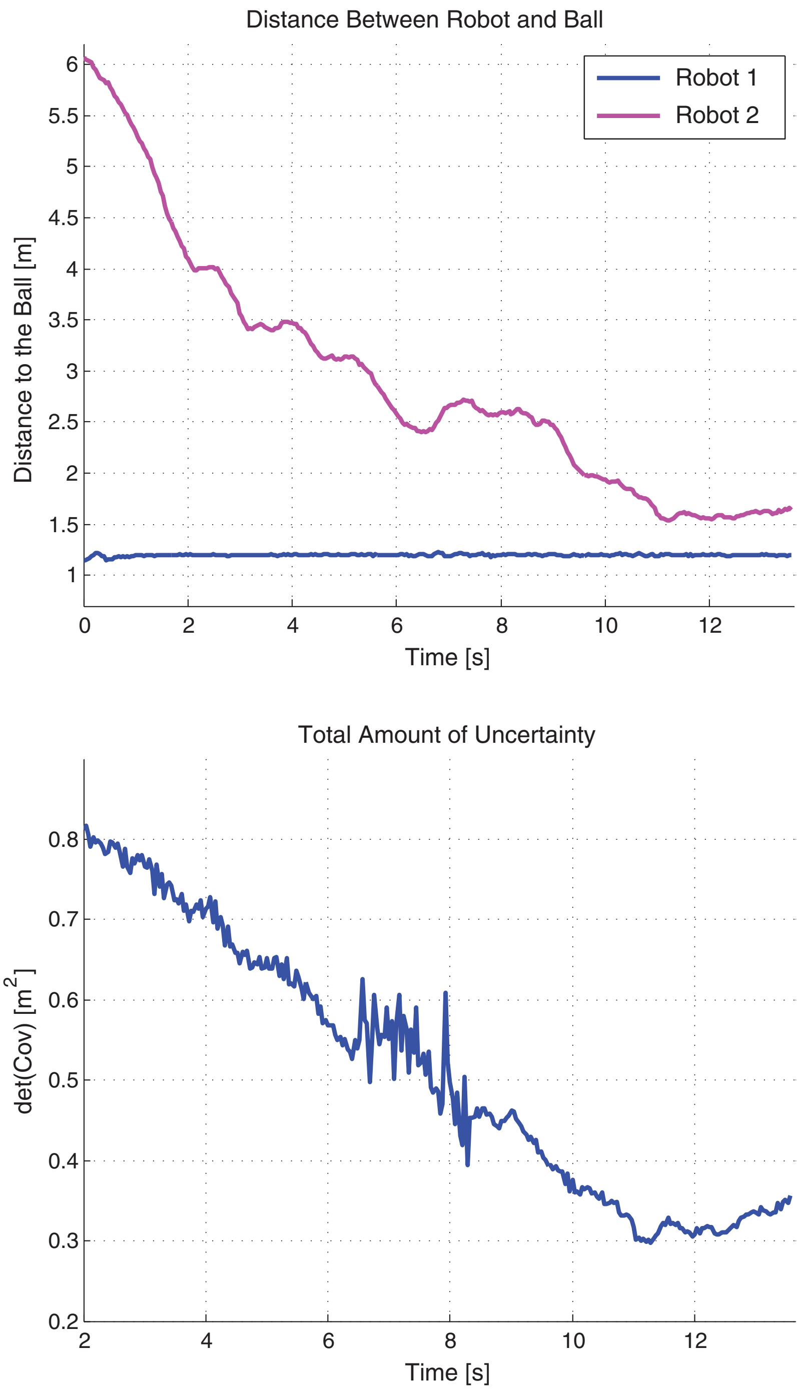

Fig. 12. Real experiment 2 - distance between robot and determinant of $\Sigma^{\perp}_{\text{Merged}}$.

robots' movements are presented in Fig. 9 and in the video **RealExperiment1** that shows that robot 2 was successful in leaving the entrapment situation and that no collisions between robots occurred.

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. 10.

Analyzing both video and the Plot XY presented in the Fig. 9 the path made by robot 2 can be understood. During the convergence, robot 2 gets trapped between the obstacle, the end of the field and robot 1, which stood in front of robot 2. Then, robot 2 starts searching for a way through, always trying to converge to the target. As the minimization of the covariance is cooperative, robot 1 moves itself into another pose allowing robot 2 to pass and converge to the target. It can be seen

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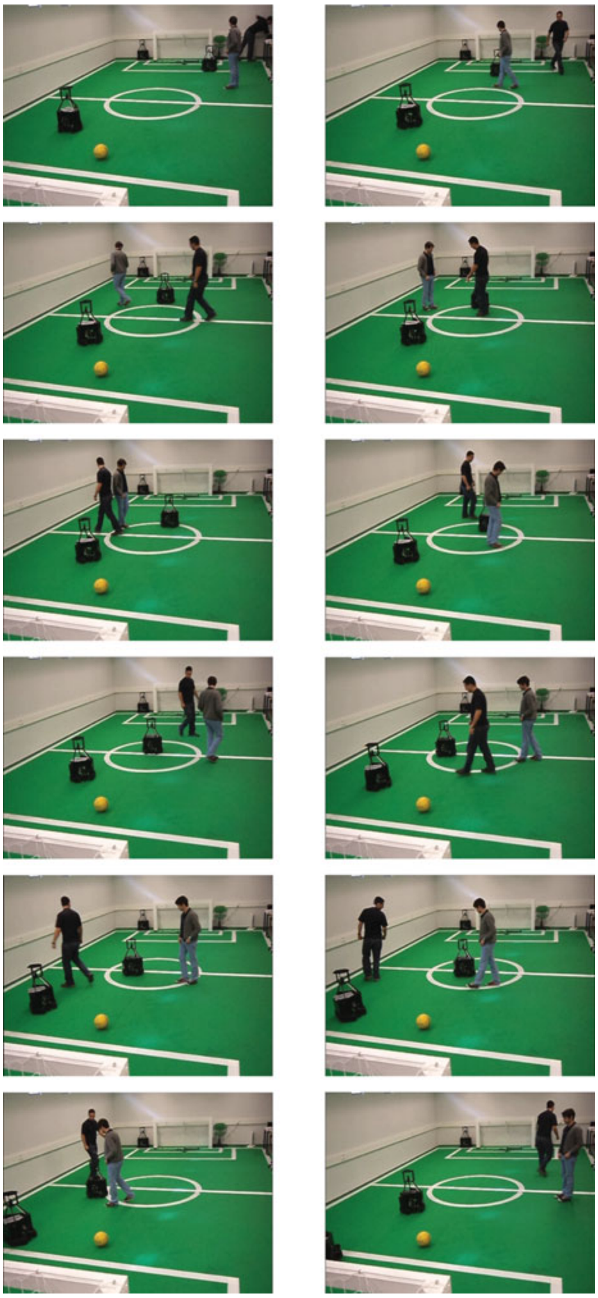

Fig. 13. Real experiment 2.

through Fig. 9 that in the real experiment the convergence of both robots towards the target was accomplished.

In the convergence, it is common to see small errors in the distance between the robots and the target. Those errors are explained by a few small vision problems that exist in the system (even after calibration) and which create errors in the localization of the target in the robot's frame. Furthermore, each robot has small localization errors that summed with the vision errors generate the errors in the world frame and therefore each robot sees its ball in a different position. Finally, all the balls are then fused in the CTE and a fused target is generated and spread through RTDB, not eliminating the distance errors completely.

4.2.2. Real experiment 2. This last experiments repeats the crowded environment in simulation 2. The objective is to converge robot 2 towards the ball. The robot leader (robot 1) is near the ball and it passes the target's coordinates to the other robot. The two persons passing through the robot's path are considered as mobile obstacles. The robot sees their legs and considered as black blobs avoiding them as any other obstacle. The path made by the robots can be seen in Fig. 11. The graph of the distance shows the robots' convergence towards the target. The covariance graph, starting from a distance where both robots see the ball (from 2s on) is also presented containing some noise due to the temporarily obstruction made by the obstacles in robot 2 target observation.

A graph with the distance between the robot and the ball as well as the minimization of the merged covariance's determinant can be seen in Fig. 12. Furthermore, the screen shots of the experiments showing the robot's movement and the obstacles' movement are presented in Fig. 13. Moreover, the video **RealExperiment2** also shows that no collisions happened. Note that in this experiments, as there is no obstacles pushing the robots afar, they put themselves in the ideal position for the merged covariance minimization.

5. Conclusion

This paper had the main objective of discussing the use of the proposed approach using artificial potential fields (APF) considered as a term of the nonlinear model predictive formation control's cost function, in order to avoid static or moving obstacles. As the NMPFC already minimizes a cost function, the APF approach made feasible the solution for the obstacles and mates avoidance problem as a terms of the NMPFC cost function.

Another contribution was introduced as a switching approach that, in cases of singularities, uses a modified version of the A* path planner in order to exit the entrapment situation. The results demonstrated the efficiency of this approach in formation control when applied to the active target tracking problem, using the NMPFC cost function by avoiding successfully the obstacles in simulations and experiments with real robots. The crowded environment demonstrated the obstacle avoidance capability regarding mobile obstacles. However, the APF approach also has its draw backs regarding concave obstacles where local minima may occur. In such situations, the modified A* algorithm proved to be a feasible temporary alternative.

Finally, it can be concluded that despite the fact that in a single robot situation, a global path planner would have better results in obstacle avoidance problem, when considering a formation of a multi-robot system, this approach proved to be a better choice. This is due to the fact that the formation uses only one cost function to minimize both formation behavior terms that perform the convergence towards a target and the obstacle/mate avoidance terms.

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