Information Seeking and Model Predictive Control of A Cooperative Robot Swarm*

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Abstract: In this paper, we propose a cooperative multi-robot control system, operating in an unfamiliar or unstructured environment. We focus on a robust model predictive control (robust-MPC) framework that enables robotic agents to operate in uncertain environments, and study the effect of observation uncertainties that arise from sensor noise on cooperative control performance. The proposed system relies on cooperative observation based on an information seeking theory, in which the system not only can compensate uncertainty, but also takes actions to mitigate it. We carry out a case study that demonstrates a multi-robot collision avoidance scenario in an unknown environment. Simulation results show that the combination of robust-MPC methods and cooperative observation enables the cooperative multi-robot system to move efficiently and reach the goal faster than an uncooperative scenario.

Keywords: Cooperative observation, estimation, robust control, robotic swarms

1. INTRODUCTION

The recent developments in robotics technology raise the expectation of numerous robotic applications such as monitoring, surveillance, and disaster response (Fig. 1). In these applications, robots often need to work in unfamiliar or unstructured environments and be able to operate under a large set of uncertainties.

Focusing on the control mechanisms for a single robot, robust model predictive control (robust-MPC) has been shown to be an effective control method to deal with such uncertainties [1]. The MPC approach predicts future states of robots and obstacles in a given environment over a finite horizon, and determines the control inputs of robots so that any subsequent predicted conditions will turn out to be most optimal. The performance, of course, depends on the accuracy of the predicted situations. Furthermore, the robust-MPC framework additionally predicts the reachability sets of those future states and finds the control inputs that satisfy desired constraints on the reachability sets. Although robust-MPC enables robots to work in considerably uncertain environments, the performance of such robots would still heavily depend on the level of uncertainty, mainly due to the very conservative nature of the robust-MPC control approach. This uncertainty is intrinsic to the relative topology of the robots and the obstacles, and in general, cannot be compensated for with computational methods alone. In order to optimize the performance of robust-MPC, it would be necessary to mitigate the level of uncertainty in the environment by cooperative exploration.

The idea of robotic swarms has been explored extensively in numerous areas of biology [2], mathematics [3, 4] as well as other fields. It has been shown that a swarm of robots working collectively rather than individually can be more efficient for information gathering to achieve a feasible solution to a given task. In other words, we could envision the swarm computational approach to be carried out in a massively decentralized fashion for the sake of robustness, as well as for faster algorithmic convergence and speedup in problem solving.

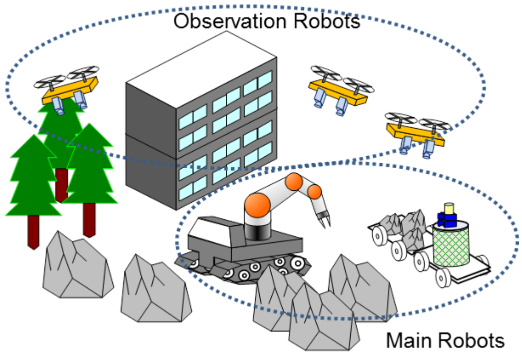

Fig.1 Robotic application in outdoor environment

In this paper, we study a multi-robot system that has the ability to carry out information seeking in a rather unstructured environment by utilizing a robust-MPC based control approach. In order for us to fully employ information seeking behaviors within our system, we consider a mutual information based control objective [3, 4]. Our focus is to demonstrate how information seeking behaviors of a cooperative robotic swarm can positively contribute to higher-level control task carried out by robust-MPC. Our work is applicable to several areas in which multi-robot systems not only perform information seeking, but also carry out a hybrid of multi-objective control patterns, for which rapid prototyping and on-line repurposing of control objectives become crucial.

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2. FRAMEWORK OF ROBOT SWARM

2.1 Main framework

Robotic swarm operation in uncertain environments is a broad area of research. Consider, for example, a disaster response scenario, in which a team of robotic vehicles are to carry out safety assessment and search and rescue missions, as depicted in Fig. 1. In this scenario, manipulators and transporters, which have specific duties, are labeled as the "main robots". Aside from these, we consider a team of "observation robots," which are responsible for cooperatively exploring the environment. The control flow for each robot is depicted in Fig. 2. The main robots and observation robots are subject to the same workflow, but they are subject to robot-specific control objective functions.

2.2 Measurement and estimation

Robots, as those aforementioned, can be equipped with one or many sensors such as cameras, laser rangefinders, and ultrasonic sensors. In the proposed system, measurements from these sensors are broadcast among all robots. We use particle filtering to synthesize received measurements and perform target state estimation, individually for each robot. Note that this framework can be extended to apply for multiple objects using estimation methods such as JPDAF [5]. It is also possible that the state of the robot itself is simultaneously estimated with the state of external objects using SLAM (Simultaneous Localization and Mapping) techniques.

In this paper, we consider the collision avoidance scenario shown in Fig. 3, where a robot equipped with a range-only sensor is to estimate the position and velocity of a non-stationary obstacle. In this formulation, the state-space model of the particle filter is given by

$$X_t = [Po_t, Vo_t]^T,$$
$$X_{t+1} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} Po_t \\ Vo_t \end{bmatrix} + w_t, \qquad (1)$$
$$z_t = \|Pr_t - Po_t\|_2 + \eta_t,$$

where Po_t, Vo_t are the position and velocity of the obstacle, respectively, w_t and η_t denote the process and measurement noise, and Pr_t is a position of the robot.

2.3 Optimal control for the main robot

In the collision avoidance scenario shown in Fig. 3, the main robot tries to move from a starting point in 2-D space to a final checkpoint, respectively chosen to be (150, 0) and (0, 0), keeping the distance to the obstacle larger than 10 m. The control input to the main robot is an acceleration input, obtained by solving an optimization problem given by

$$\min_U \sum_{k=1}^{N} f_0 = \min_U \sum_{k=1}^{N} |Pr_{t+k}|^2 , \qquad (2)$$

subject to

$$f_1 + \alpha \cdot \sigma_{t+k} \le 0 \qquad (f_1 = D^2 - |Pr_{t+k} - Po_{t+k}|^2),$$
$$f_2 = |V_{t+k}| - Vmax \le 0,$$
$$f_3 = |U_{t+k}| - Amax \le 0,$$

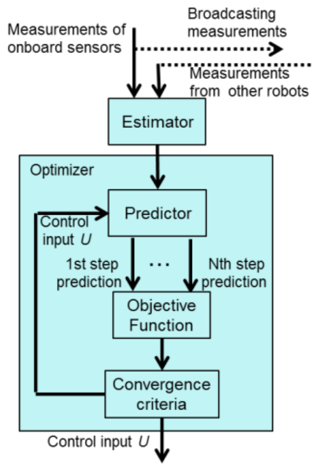

Fig.2 Robot control flow

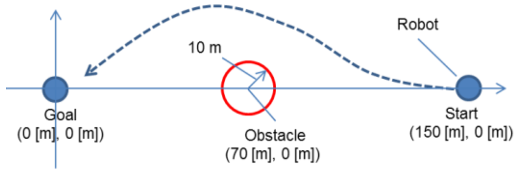

Fig.3 Collision avoidance scenario trajectory scheme

where V_t is the velocity and U_t is the acceleration of the main robot. The state variables of the robot (Pr_{t+k}, V_{t+k}) are predicted using current state and control inputs of future steps U_{t+k}. Current position of the obstacle Po_t is estimated by a distribution of particles, which is obtained from the particle filter at each time step.

f_0 is the squared Euclidean distance from current position of the robot to the goal. f_1 is a collision avoidance constraint. If the robot is within a distance D to the obstacle, then f_1 will be active. f_2 and f_3 are box constraints on the velocity and acceleration of the main robot, respectively. D is a safety margin on distance to the obstacle, *Vmax* is the maximum velocity, and *Amax* is the maximum acceleration, are all chosen with respect to the hardware configuration and functional capabilities of the robot. σ_t is a variance of the constraint function f_1 which is given by

$$\sigma_t = \sqrt{\left(\frac{\partial f1}{\partial Po_t}\right) \cdot C_t \cdot \left(\frac{\partial f1}{\partial Po_t}\right)^T} , \qquad (3)$$

where C_t is a covariance matrix of Po_t computed from the distribution of particles. If the obstacle's position Po_t is unknown, σ_t is large so that the constraint f_1 is tightened. The robot will move away from the obstacle proportionally to the scaling factor α.

Optimization problem (2) can be solved using general constrained optimization theory. Specifically, we use the interior point barrier-method [6] to solve it.

2.4 Optimal control for the observation robots

Unlike the case for the main robot, the control objective of the observation robots is not set to be a pursuit goal. The objective instead is to provide as much information as possible about the unknown environment to the main robots by utilizing their on-board sensors and dynamic capabilities.

For the control of observation robots, we use Eq. (4) as the objective function instead of Eq. (1). Here, I_t is the mutual information between the estimated state of the obstacle and the future measurements of the observation robots, given by Eq. (5). The function P in Eq. (5) is a conditional probability density function, $z_{t,k}$ and $z_{t,j}$ are the prediction of measurements if the robot measures the particle k and j, respectively, and η_t is an assumption of measurement noise. More details about information seeking using mutual information are described in [3, 4]. Using the objective function given by Eq. (4), observation robots can be controlled to maximize the expected future mutual information, or equivalently, to minimize the expected future uncertainty of the obstacle's position estimate (Fig. 4).

$$\min_{U}\left\{-\sum_{k=1}^{N} I_{t+k}\right\} \tag{4}$$

subject to

$$f_1+\alpha\cdot\sigma_{t+k}\le 0 \qquad (f_1=D^2-|Pr_{t+k}-Po_{t+k}|^2),$$
$$f_2=|V_{t+k}|-Vmax\le 0\,,$$
$$f_3=|U_{t+k}|-Amax\le 0\,,$$

$$M_t\approx-\sum_{k=1}^{N} w_{t,k}log\sum_{j=1}^{N} w_{t,j}\,P\left(z_{t,k};z_{t,j},\,\eta_t\right) \tag{5}$$

3. CASE STUDY: COLLISION AVOIDANCE

3.1 Experimental Setup

In this section, we explore a cooperative multi-robot swarm, which has the purpose of reaching a target point in the presence of obstacles of unknown dynamics. The simulation parameters are summarized in Tables 1 and 2. Case 1 describes a model of a traditional standalone robot, which does not consider measurement uncertainty. Case 2 describes a robot that utilizes robust-MPC. Cases 3 and 4 are cooperative systems, which can proactively decrease the uncertainty using observation robots.

The simulations of each case developed using Ptolemy II [7], which is a Java-based actor-oriented graphical modeling platform that offers extensive actor libraries for machine learning and optimization tools [8]. At each time step, the position of the obstacle is calculated with additive Gaussian noise η_t and then sent to the control system. To simulate a range-only measurement sensor, σ_b is set to be a large value, which approximates the uncertainty of the obstacle as an ellipse in 2-D space, as illustrated in Fig. 4.

3.2 Result of case 1: traditional robot

The trajectories corresponding to all four scenarios are illustrated in Fig. 5. The robot without robustness is shown not to be able to avoid the obstacle all the times. As shown in Fig. 6, before the robot comes close to the obstacle, those particles associated with the obstacle were spread widely, hence the drastic change in the distribution center of the particle ensemble. This

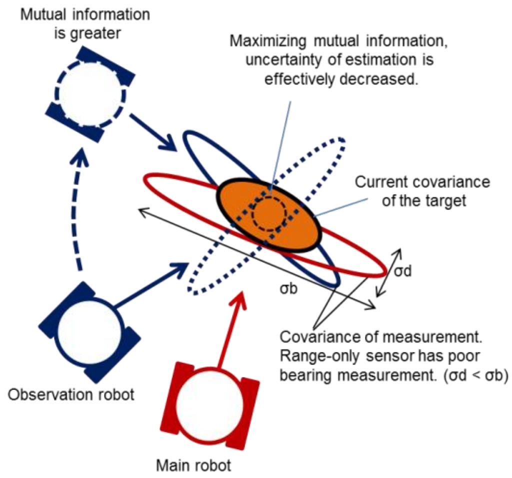

Fig.4 Information seeking using mutual information

Table 1 Simulation condition

	Robustness factor α	The number of Obs. robot
Case 1	0	0
Case 2	1	0
Case 3	1	1
Case 4	1	2

Table 2 Parameter settings for simulation scenarios

$Vmax$	40 m/s
$Amax$	40 m/s^2
Measurement noise η_t	Distance σd=1 m, Bearing σb=10 m
Prediction time horizon	N = 20 steps 1step = 0.1 s

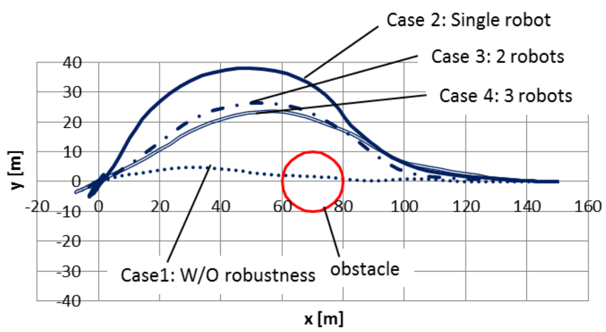

Fig.5 Robot trajectories under different control scenarios

estimation error causes a large prediction error in the future state of the robot, consequently leading it straight to the obstacle. When operating a robot in uncertain environments, problems of the aforementioned type will most likely occur at some point. In general, smart robots working in unfamiliar environments would need to have that extra capability of survival in order to be able to avoid not only any encountered obstacle, but also all other unforeseeable situations that may unexpectedly and rather dynamically come about.

3.3 Result of case 2: robust controlled robot

As shown in Fig. 5, given the level of uncertainty, the robot of case 2 can safely avoid the obstacle. However,

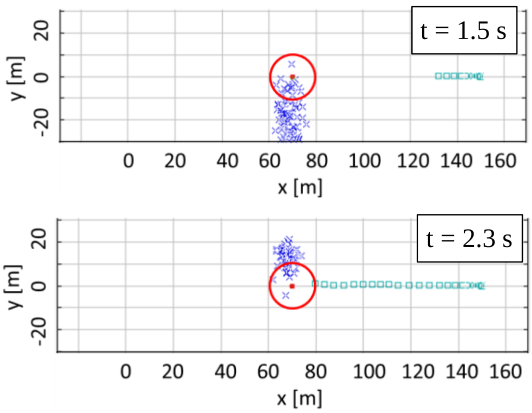

Fig.6 Particles estimating obstacle position in Case 1

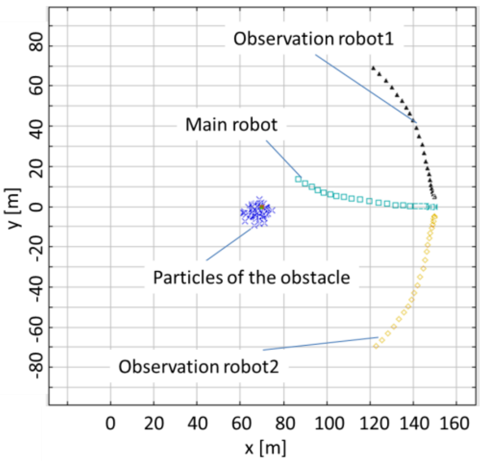

Fig.7 Trajectory of the robot swarm in case 4

given the wide distribution of particles as shown in Fig. 6, the robot would need to travel the furthest in order to avoid the restricted area of particle distribution.

The result of this case implies that the robot can arrive at its goal faster provided the high accuracy of its sensors. However, general sensors have to deal with noise all the time especially in outdoor scenarios. This is a tough problem to completely resolve, but in general, synthesizing multiple measurements would certainly reduce some of those uncertainties.

3.4 Result of case 3: the robot swarm

In the presence of two robots, we notice the total distance covered by the main robot until the target point is shorter than that of the single robot of case 2. The set of observation robots as shown in Fig. 7 have their own separate trajectories. Such trajectories would allow for obstacle observation from different locations, at a distance from the main robot. As a result, we notice that the obstacle position is estimated to be a relatively small and precise area within the search space. Reduction in the size of the particle area turns out to have some interactive benefits between the observation robots and the main robot. Specifically, this could directly lead to a form of constraint relaxation on the main robot, and in turn, allows the main robot to follow a less conservative yet safe trajectory around the obstacle.

Comparing with case 3, the trajectory of the main robot of case 4 was slightly shorter (see Fig. 5). This result implies that with the increase in the number of observation robots, more information is available and the main robot can move to the goal more properly. When considering more complicated situations, there is a possibility that three or more observation robots are needed. For example, some robots have different kind of sensors such as cameras and laser range-finders and measurement noises of each sensor can vary. In that case, a large number of observation robots, a cooperative robot swarm, would be beneficial to reduce uncertainty further, and to provide a stable and high performing set of main robots.

4. CONCLUSION AND FUTURE WORK

In this paper, we proposed a new multi-robot control system that works in uncertain environments. The proposed system operates multiple robots to decrease sensed uncertainty and achieve high performance. Simulation studies have shown that the observation robots play a crucial role in enhancing the capabilities of main robots in order to avoid obstacles and safely arrive at the target points in shorter times.

Future work includes evaluation of the proposed system in a more complex environment, which considers varying sensor noise levels for each robot, as well as other noise sources such as obstacle motion, sensor faults, and communication delays. Particularly, distributed control techniques will be explored, which reduces the local dependency to information from other robots under communication imperfections.

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