STRATEGY BASED ON MACHINE LEARNING FOR THE CONTROL OF A RIGID FORMATION IN A MULTI-ROBOTS FRAME

Ting Wang, Christophe Sabourin and Kurosh Madani
Signals, Images, and Intelligent Systems Laboratory (LISSI / EA 3956)
Paris Est University, Senart Institute of Technology, Avenue Pierre Point, 77127 Lieusaint, France

Keywords: Multi-robot systems, Formation control, Learning and adaptive Systems, Intelligent logistic application.

Abstract: Many applications can benefit from multi-robot systems like warehouse management, industrial assembling, military applications, daily tasks. In this paper, we describe a new approach for the control of a formation of robots. In the proposed solution, we consider the formation as a single robot and our work focus on how to control the formation. We suppose there are virtual rigid links between all robots and all robots perform the same task in synchronous manner.

1 INTRODUCTION

Today, and in the future, many applications, like warehouse management, industrial assembling, military applications, daily tasks, could benefit from multi-robot systems (Parker, 2008), (Cao et al., 1997). However, the design of a control strategy for the multi-robot systems needs cooperation and coordination between all robots. In this context, one of goals of our researches is to design control strategies for multi-robot systems mainly for industrial applications. For example, multi-robot systems are used in logistic application (Wurman et al., 2008), where a lot of small robots are used transport some objects. This approach seems very interesting but it has some limitations. All of robots have individual behaviors and all of robots are controlled by a supervisor. The goal of this paper is to present our first investigation in the domain of the multi-robot systems for logistic applications and more especially for collaborations between several robots carrying a load.

The proposed work is very close from studies about formation control of robots. But generally, in all previous publications about formation control of robots, researches focused on the control of all robots in order to maintain the formation (for expamle (Mastellone et al., 2008) (Barfoot and Clark, 2004)). In this work, we focus on how to control the formation and we consider the formation like a single robot. Furthermore, we suppose there is some virtual rigid links between all robots and that all robots can perform the same task in a synchronous manner. In addition, in order to use our approach in real time, we propose a solution based on the image processing and a machine learning. As result, we show that it is possible to move a rigid formation of robots in a constraint environment.

The reminder of this paper is organized as follows. In section 2, we describe the proposed approach and mainly we expose the solution that we used to control the formation. The learning process used to compute the path planning is outlined in detail in section 3. The simulation results have showed in section 4. Section 5 gives conclusion and presents further works.

2 CONTROL STRATEGY FOR THE ROBOTS' FORMATION

The use of a multi-robot systems to transport bulky objects is an elegant solution for this kind of problem and that is a very flexible solution. Effectively, sometimes this task needs to design specific vehicles according to some constraints which come from the object to carry.

In this paper, and without any loss of generality, we will consider only a formation with three robots (see Fig.1). Furthermore, it must be pointed out that in this work we focus only on the high level control. And we consider that there is a low level control which is able to maintain the rigidity in the forma-

Wang T., Sabourin C. and Madani K..
STRATEGY BASED ON MACHINE LEARNING FOR THE CONTROL OF A RIGID FORMATION IN A MULTI-ROBOTS FRAME.
DOI: 10.5220/0003535503000303
In *Proceedings of the 8th International Conference on Informatics in Control, Automation and Robotics* (ICINCO-2011), pages 300-303
ISBN: 978-989-8425-75-1

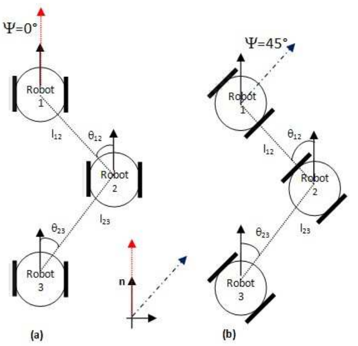

Figure 1: Schematic description of a rigid formation with three wheeled robots. The relative distance between two robots is a constant value and all robots are the same orientation ($\psi = 0°$ figure (a), $\psi = 45°$ figure (b)).

tion of robots. This formation is formed by wheeled robots moving in a plane. Each robot may be one nonholonome robot (e.g. unicycle-type mobile) or another kinds (e.g. omni-directional).

The modeling used to describe the formation (represented on the Fig.1) is based on the following concepts:

- There is a reference robot in the formation (e.g. robot 1 on the Fig.1). The both position and orientation of this robot corresponds to the both position and orientation of the formation according to an absolute frame. It must be pointed out that the reference robot is not necessarily a leader robot.
- The position of the other robots i are defined according to the position of robots i-1. Two parameters are used to specify this position. There are the relative distance between two robots (e.g. l_{12} and l_{23} on the Fig.1) and the absolute angle between the orientation of the robot and a normal direction (e.g. θ_{12} and θ_{23} on the Fig.1).
- The formation is rigid which means that the relative distance between two robots is a constant value and all robots have the same orientation. It must be noticed that the orientation of formation (ψ) is independent of the angle ϕ used to describe the relative position between two robots ($\psi = 0°$ Fig.1(a), $\psi = 45°$ Fig.1(b)).

The state of the formation is given by the position of the reference robots (e.g. the robot number 1) and the orientation of the formation. We define 8 possible orientations (see Fig.2) dependent directly of the angle θ: $\theta = 0°$ for the formation 1, $\theta = 45°$ for the formation 2, $\theta = 90°$ for the formation 3, and so on. Consequently, this orientation is independent of the angle ψ. For each orientation, we define height possible actions (from 1 to 8) (see Figure 3). These

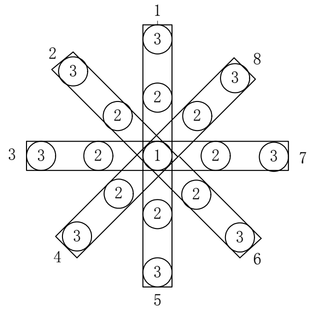

Figure 2: Schematic description of the 8 formations.

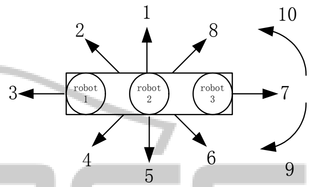

Figure 3: Actions used to control the formation.

actions correspond to the directions (angle ψ) allowing to move the formation of robots. Two other actions allow to do a rotation of the formation (Action 9 and 10 are the clockwise and anti clockwise rotation action respectively). Because we consider nonholonomic robots, if the rigid formation needs to move in a desired direction (for example formation 7 and action 3), each robot in the formation simultaneously rotates to the desired direction by using an orientation control and after go forwards in the desired direction.

3 PATH PLANNING FOR A RIGID FORMATION OF ROBOTS

Based on the previous description of our control strategy, the problem is now how to compute the path planning (to find action like ”forwards”, ”left”, and so on) to move the formation from an initial point to a goal point in a constraint environment (obstacle avoidance, narrow path, etc..). In order to design online approach for real-time application, we have based our concept on two levels. The first one allows us to get the equivalent quantified environment, and the second carry out a learning process in order to find the set of the best actions.

3.1 Image Processing

In order to get automatically numerical information allowing to represent environment, we have developed an approach based on image processing. This procedure uses the following process:

Figure 4: Picture of the virtual environment given by a virtual camera located at the top of environment.

- Taking the photo of the environment. It should be noticed that in order to simplify, in the first time, we consider we have a virtual camera located at the top of environment (see for example Fig.4).
- Modify the RGB image to the gray scale image, and convert the gray image into a binary image with a suitable threshold value.
- The last step allows to describe environment by a binary matrix, in which 1 represents obstacles and 0 is free path.

After the image processing, it is possible to get the equivalent quantified environment (see Fig.5). In this example, the environment is divided into 100 states where each state is a square with sides 30cm. For the quantified environment, the obstacles are marked with red stars. The formation is composed with a reference robot (the robot 1 represented like a solid black dot on the Fig.5) and other robots (robot 2 and 3 represented like black circle). In initial position, the robots stand in the position A which is in the state $[6;10]$. The final state position B is in state $[4;10]$.

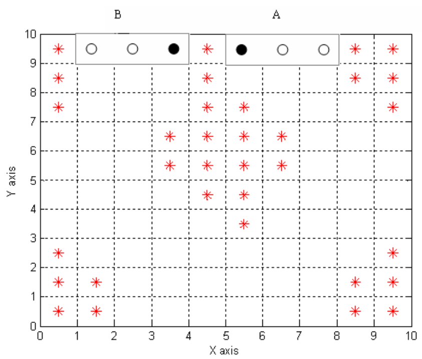

Figure 5: Equivalent quantified environment representation: the obstacles are marked with red stars, the reference robot is represented like a solid black dot and other robots represented like black circle.

3.2 Q Learning

Now, our aim is to find a solution allowing to move the three robots from point A to point B in conserving a virtual rigid formation (a line in this case). As has been noted in the section 3.1, the environment may be described by a matrix E(10×10). This matrix contains information about the position of the obstacles. But, it is not sufficient to describe the full state S. Effectively, one state should be composed of two information which are the position of the reference robot, and the kind of the formation. Consequently, the size of the set S is equal to $10\times10\times8$

On the base of the last description of the state S, and being given that we consider the formation like only one robot, it is possible to look for the succession of actions in order to move the formation from the point A to another point B. To solve this problem, one solution consists to use a reinforcement learning. The goal of the reinforcement learning algorithm is to find the action which maximizes a reinforcement signal. The reinforcement signal provides an indication of the interest of last chosen actions. Q-Learning, proposed by Watkins (Sutton and Barto, 1998), is a good way to use reinforcement learning strategy.

4 SIMULATION

In this section, we present results of simulation for the example described in the section 3. The frame of this simulated environment is composed of three robots KheperaIII[1] and a top camera. Simulations have been performed by using software Webots [2] and controllers have been designed with the software Matlab [3].

As described in the previous section, the world is a square with 3 meters sides. And it is divided into 100 small squares, where each squares (0.3x0.3 m) represents possible position of one robot. Concerning the KheperaIII, we suppose that robots are always located in the center of the square. And we suppose that standard robot 1 permanently moves from the position of one center of the square to another. The other two robots rotate around the standard robot so as to change the formation. The radii are $0.3m$ and $0.6m$ respectively by taking the reference robot as the reference frame. Throughout the whole process, robots run the same operation synchronously. When the path planning is computed, then it is possible to compute the reference trajectories for the robots of the formation. It is be noticed that as we use nonholonomic

[1] www.k-team.com/
[2] www.cyberbotics.com/
[3] www.mathworks.com/

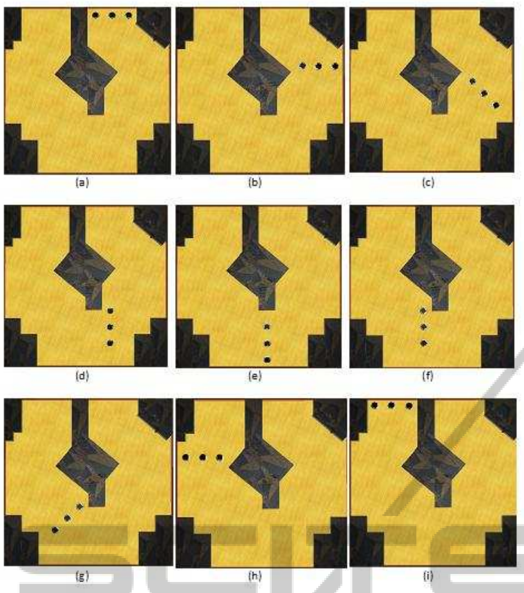

Figure 6: Snapshot of simulation's results. The virtual environment is composed of three robots KheperaIII which have to move by avoiding obstacles but with a rigid formation.

robots, trajectories are decomposed into rotations and linear motions. Fig.6 shows snapshot of simulation's results. As depicted on the pictures, we can observe that the three robots move from the initial point to the final point in keeping the rigid formation. The possible actions (from 1 to 10) are chosen according to the environment constraints.

The Fig.6(a) shows the initial position of robots, and their formation (formation 7). After a series of translation actions (action 6), robots arrive in the position showing by Fig.6(b). Then, robots must change their formation in order to avoid obstacles. Fig.6 (c) and Fig.6 (d) show the rotation actions. Then robots with formation 5 (in vertical) move to the upper left by three translation actions. The beginning and final position are Fig.6 (e) and Fig.6 (f). After that, both the translation actions and rotation actions have done, and the two snapshot of the motion in this stage are Fig.6 (g) and Fig.6 (h). At the end of the path, robots rotate back to horizontal orientation (with formation 3) but on the opposite to the initial formation 7, in which robot 1 is on the right of the formation. And robots translate again along the upper left till they arrive to the top left of the environment. The final position is in Fig.6 (i) with formation 3.

5 CONCLUSIONS

In this paper, we have described a new approach for the control of a rigid formation of robots in the frame of logistic applications. In the proposed solution, we have considered the formation as a single robot and our work has focused on how to control the formation. To use our approach in real-time, we have proposed a solution based on the image processing and a machine learning. As result, we have shown that it was possible to move a rigid formation of robots between two points in a constraint environment. Some results about simulation have proven the efficiency of the proposed method.

Future works will focus on the improvement of the proposed method, namely on the collaboration between all agents. And we will investigate realistic problems in the domain of industrial application.

ACKNOWLEDGEMENTS

This work was supported by a doctoral fellowship from the China Scholarship Council (CSC). Authors wish to express their gratitude to CSC.

REFERENCES

Barfoot, T. D. and Clark, C. M. (2004). Motion planning for formations of mobile robots. *Robotics and Autonomous Systems*, 46(2):65 – 78.

Cao, Y. U., Fukunaga, A. S., and Kahng, A. (1997). Cooperative mobile robotics: Antecedents and directions. *Autonomous Robots*, 4:7–27.

Mastellone, S., Stipanovic, D. M., Graunke, C. R., Intlekofer, K. A., and Spong, M. W. (2008). Formation control and collision avoidance for multi-agent non-holonomic systems: Theory and experiments. *I. J. Robotic Res.*, 27(1):107–126.

Parker, L. E. (2008). Multiple mobile robot systems. In Siciliano, B. and Khatib, O., editors, *Springer Handbook of Robotics*, pages 921–941. Springer Berlin Heidelberg.

Sutton, R. S. and Barto, A. G. (1998). *Reinforcement Learning: An Introduction*. The MIT Press.

Wurman, P. R., Andrea, R. D., and Mountz, M. (2008). Coordinating hundreds of cooperative, autonomous vehicles in warehouses. *AI Magazine*, 29(1):9–20.