

# MRL Team Description Paper for Virtual Robots Competition 2013

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**Abstract.** This paper describes a short review of the MRL team's work developed for participating in RoboCup2013 Virtual Robots Competitions. It includes parts such as SLAM, Autonomous Exploration, Multi Agent Coordination and Exploration, Robot Control, Image Enhancement, ROS.

## 1 Introduction

Nowadays Robotic and Artificial Intelligence are in the center of attention of many researchers. USARSim provides us with an environment in which the conjunction of these two fields occurs. In this environment, a disaster is being simulated in indoor and outdoor scenarios. The goal is to gather a map of unknown environment which would provide information about the situation, victims. To overcome the goal, a combination of the state of the art algorithms of different fields needs to be implemented. These fields include Localization, Mapping, Image Processing, Robot Navigation, Robot Communication and Control, Multi-Robot Exploration and Coordination.

Our team members and their contributions in team are:

- SLAM : Sanaz Taleghani, Mohsen Akbari
- Autonomous Exploration : Mohammad.H Shayesteh, Sanaz Taleghani, Sara Heshemi
- Multi Agent Exploration : Saeid Samizade, Mohammad.H Shayesteh, Fatemeh Sistani
- Control of mobile robot : Jalal Najafi, Saeid Samizade
- Image Enhancement : Sara Hashemi, Atoosa Hashemi
- ROS : Mohammad.H Shayesteh, Atoosa Hashemi

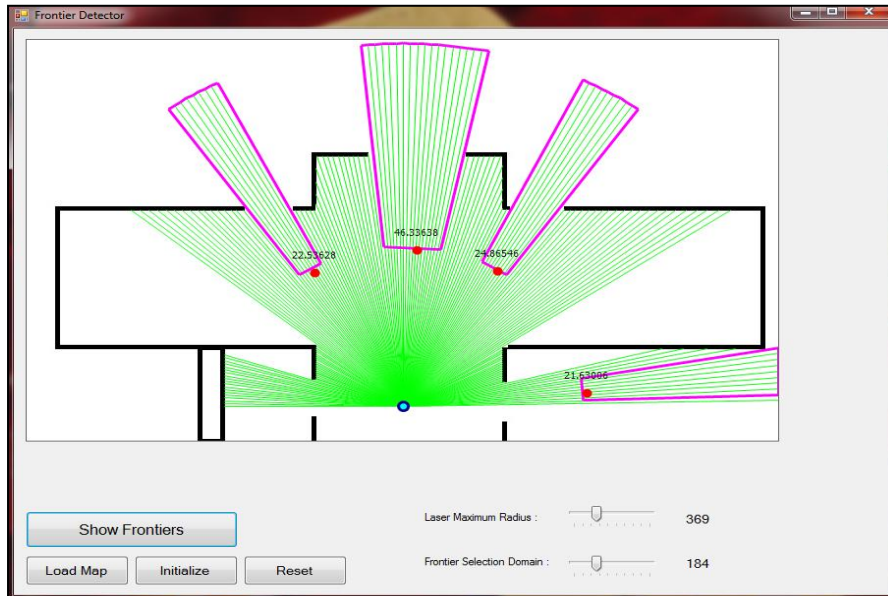


## 4 Multi Agent Exploration

We design a frontier based method [3] for multi agent exploration. When a robot performs frontier detecting process, it uses the range scan data and detects each sequence of laser beams that return a distance more than a specific value, as a frontier and put frontiers location between the sequence's start and end. After it guess a weight for each frontier with three Parameters such as ( $\theta$ , A, D).

where  $\theta$  is degree of frontier degree, A parameter is free area to explore the frontier behind and D parameter is the size of the entrance. See Figure 2.

$$W_f = w_0 + w_1\theta + w_2D + w_3A$$



**Fig. 2.** Calculating weights for Frontiers

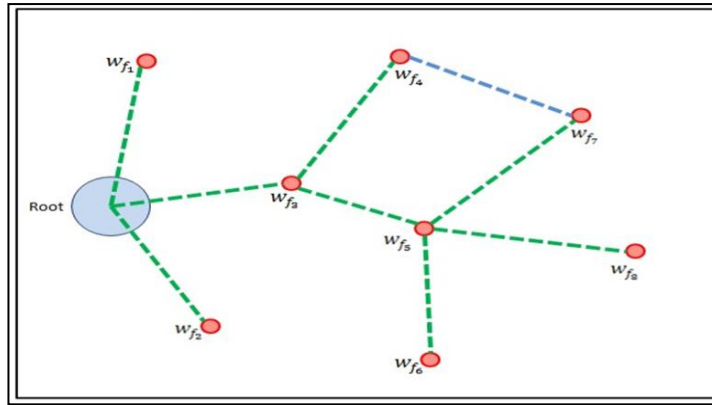
Where  $w_0$  to  $w_3$  are constant values. After visiting the frontier by a robot, its real weight will calculate and replace. We decided to minimize the subtraction between new value and old value by adjusting  $w_0$  to  $w_3$  such that this problem can solve easily by LMSE (Least Mean Square Error) algorithm [4]. The method applied in LMSE, initialization frontiers weight are based on expert knowledge. Also weight can be calculated based on the mechanisms that have been proposed by visser et.al [5]

Our method is a tree based that manages robots movement in the map. In this method, each frontier will be represented by a node and each path between frontiers

with an edge. The blue circle in Fig 3 is the initial location of the robots when spawn near BS. This is root of the tree.

We assume a level for each node. The Level of root is always zero. Each frontier can be detected from a visited frontier that is its child. The level of a child is 1 unit more than its parent's level.

For example, in Fig 3.  $f_1, f_2, f_3$  have same one level,  $f_4, f_5$  have same level with two number and frontier  $f_4$  can be detected from  $f_7$  but in this case, the parent level is less known as the main parent. It means that the level of  $f_4$  is 2.



**Fig. 3.** Exploration Graph

As mentioned in the previous section, the robot after detecting new frontiers, calculates the weight with parameters. Since Robot visits the frontier, its weight is calculated according to the conditions. Our measure is the total weight of new frontiers that are obtained from it (children frontiers are unvisited). After it, all parent frontiers to root will be updated by the formula below. This formula proved as a reinforcement learning method [6].

$$w_{p_{f_i}} = w_{p_{f_i}} + \alpha [w'_{f_i} - w_{f_i}]$$

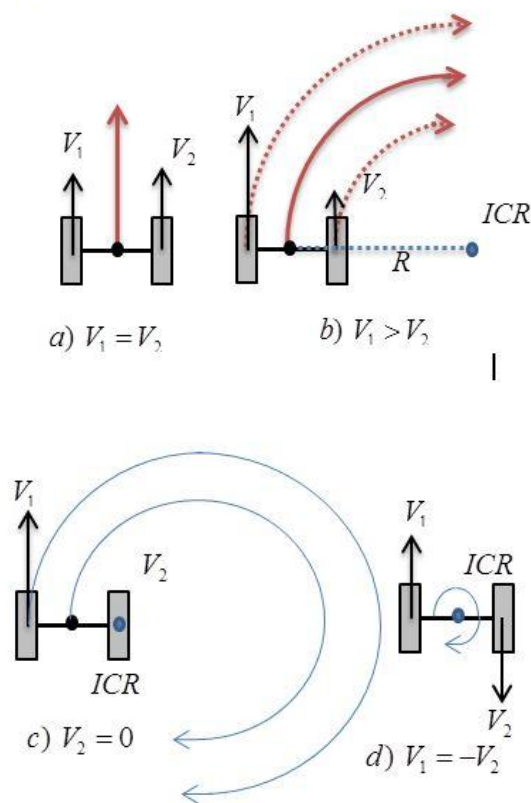
Where  $\alpha$  is a float constant value between 0 and 1 and known as learning rate. For example in Fig 1 if  $w_{f_5} = 80$ ,  $w_{f_3} = 100$  after the explored  $f_5$  total weight of  $w_{f_6}, w_{f_7}, w_{f_8}$  is given as  $w_{f_5}$ . Thus if  $w'_{f_5} = w_{f_6} + w_{f_7} + w_{f_8}$  are more than 80, a positive value is added to  $w_{p_{f_3}}$ , and this effect will be reduced to the root.

Robots will extend the tree during exploration. Each branch continues to explore the map such that the tree extends with the highest rate and Information sharing quickly between agents.

## 5 Robot Control

One of the simplest mobile robot constructions is a chassis with two fixed wheels. Understanding this construction helps you to grasp some basic kinematics of car-like robots. Usually differential drive mobile robots have an additional castor wheel as the third fulcrum. It is usually used for stability. Sometimes roller-balls can be used but from the kinematics point of view, there are no differences in calculations.

As it can rotate freely in all directions, in our calculation we can omit the castor wheel because it only has a very little influence over the robot's kinematics. In case of differential drive, to avoid slippage and have only a pure rolling motion, the robot must rotate around a point that lies on the common axis of the two driving wheels [7]. This point is known as the instantaneous center of curvature (ICC) or the instantaneous center of rotation (ICR). By changing the velocities of the two wheels, the instantaneous center of rotation will move and different trajectories will be followed (Fig. 4) [8].



**Fig. 4.** the different moving for differential drive

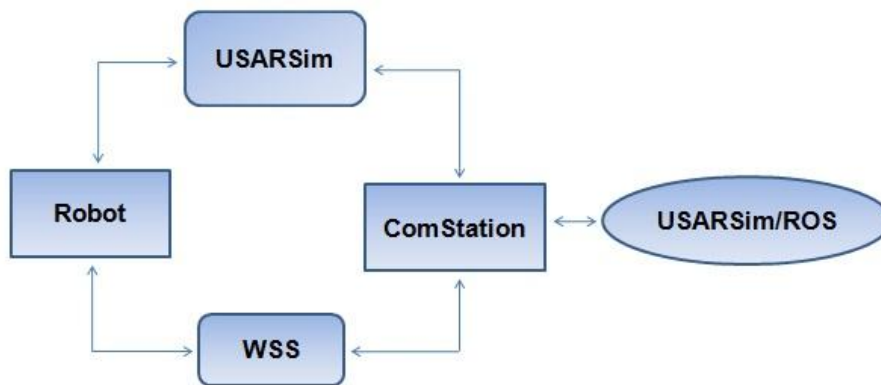
Where  $v_1$  is the left wheel's velocity along the ground, and  $v_2$  is the right wheel's velocity along the ground, and  $R$  is the signed distance from the ICR to the midpoint between the two wheels. When  $v_1$  and  $v_2$  were calculated, four states occurred (fig 4). If  $v_1$  and  $v_2$  are equal then the robot moves in a straight line (see Fig. 4a). For different values of  $v_1$  and  $v_2$ , the mobile robot does not move in a straight line but rather follows a curved trajectory around a point located at a distance  $R$  from CR (Fig. 4b), changing both the robot's position and orientation.

If one of the wheel's velocity is zeros the robot turning around wheel which has zeros velocity and follows a circle trajectory (Fig 4c). If  $v_1 = -v_2$ , then the radius  $R$  is zero and the robot rotates around ICR (it rotates in place Fig. 4d).

## 6 ROS

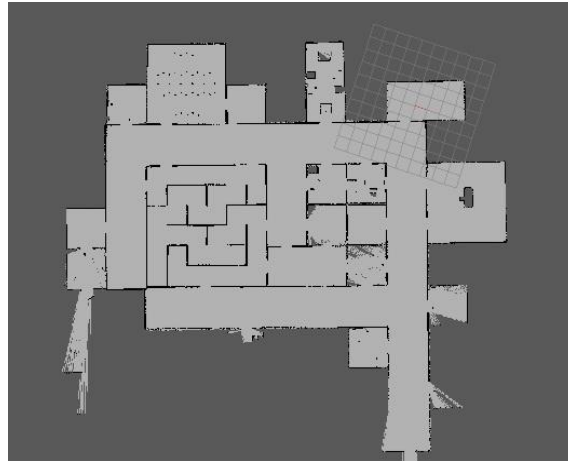
One of the most important challenges in autonomous and multi agent systems is complexity in low level modules. These kinds of problems have big effects on performance of your system in different situations. There are many solutions for these problems. One way is using from standard packages for lower layers such as ROS (Robot Operation System) packages. This package as been used in Mapping, Navigation and control modules.

Using of the ROS in virtual robot simulation needs to a wrapper and interface application such as USARSim/ROS [9,10]. As shown in Fig. 5, USARSim/ROS is used in Com Station for mapping and navigation modules.



**Fig. 5.** Architecture of autonomous system base on ROS

The robot send its data to WSS, then Com Station receives these data and gives them to USARSim/ROS; Finally USARSim/ROS package generates the map and navigation decisions. As shown in Fig. 6, the map has been generated by Gmapping package.



**Fig. 6.** Using USARSim/ROS for generating map

## 7 Image Enhancement

Since the realization of received images from smoky environment with low contrast is hard, for solving this problem we tested several algorithms such as contrast, sharpen, etc that among them equalization and normalization have best results. Equalization algorithm increases contrast in image but does not normalize values ,it is good reason for using histogram normalization.



**Fig. 7:** Comparison of contrast, sharpen and normalization

## 8 Conclusion

In this paper we summarized the main features of MRL team developed for participating in Robocup competition 2013. We improved on Autonomous challenges, Image enhancement, control of robot and other different methods are still in progress.

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