YILDIZ Team Description Paper for Virtual Robots Competition 2015

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Abstract. This paper is a short review of technologies developed by YILDIZ team for participating in RoboCup 2015 Virtual Robot Competitions. This year our focus is on improving our SLAM abilities, communication limited multi robot exploration, and automatic victim detection.

1 Introduction

Probabilistic Robotics Group of Yıldız Technical University, which consists of a team of students and academicians, has been working on autonomous robots since its establishment in 2007. Autonomous robots can perform desired tasks without continuous human guidance which is necessary for Urban Search and Rescue area [1, 2]. Last year's world championship was the fourth experience of our team on RoboCup. We took second place at Mexico RoboCup, Netherlands RoboCup and Brazilian RoboCup competitions. We have learned a lot of lessons over years as following:

- Our user interface is very useful.
- Our message routing protocol is very useful.
- Our autonomous navigation algorithm by obstacle avoidance is very useful.
- Our image enhancement algorithm is very useful.
- Our SLAM algorithm is very useful. But its distributed version should be developed.
- We should improve our air-robot localization algorithm.
- We should improve our automatic victim detection algorithm.
- We should improve our autonomous exploration algorithm especially for the communication limited areas.

This year, several developments over some of these systems and they are presented at this report.

The system is designed to have a hierarchical structure, containing different modules responsible of different jobs. Every fundamental part of the main problem divided into modules which can function independently. Normally, each of our virtual robots is intelligent enough to explore the area, find the victims and construct a map. Using multiple robots made the system more accurate and robust.

The team members and their contributions are as follows:

Control and monitor interface	: Attila Akinci
SLAM algorithm	: Attila Akinci, Muhammet Balcilar , Sirma Yavuz
Multi robot exploration	: Attila Akinci, Muhammet Balcilar, M. Fatih Amasyali
Victim Detection	: Bedir Yilmaz, Muhammet Balcilar, M. Fatih Amasyali
Supervising, system design	: Sirma Yavuz, M. Fatih Amasyali

2 System Overview

The main software modules are user interface, localization, mapping, navigation, exploration, communication and victim detection. Robots on their own have all those modules equipped and ready-to-use, there is also a multi-robot coordination module covering them all. As the ground robots we use the Pioneer 3AT and Kenaf models. The sensors to be used are determined as Hokuyo URG04L model laser scanner, camera, ultrasonic, encoder, touch, and odometry sensors. We also use Air Robots with only two camera sensors.

3 User Interface

The user interface is developed to control 16 robots at the same time as autonomous, semi-autonomous or manual and the interface consists of two forms as shown in Fig. 1(a) and Fig. 1(b).

At the Form 1 of the user interface (Fig. 1(a)), the thumbnail of all robots' camera views, the camera view and the orientation of the selected robot can be seen. The robots can be controlled by the user keyboard or the direction arrows on the Form 1. The speed of the robots can be adjusted by the controller next to the direction arrows.
Extra abilities are also placed alongside of the direction arrows like autonomous door passing, victim detection, etc. . For example door passing method provides a smoother movements when the robot decides to pass a door without control command.

At the Form 2 of the user interface (Fig. 1(b)), the map of the disaster area, the coordinates and directions of the robots, the scanned areas and obstacles can be seen. The robot to be controlled is selected from the map and navigation orders can be send via right clicking on the dynamically generated map after the robot is selected. Robots can be set as autonomous or manual using the checkbox list where is placed right side of the form. Trajectory lines of the robots can be adjusted as visible or invisible using trajectory checkbox.

Target selection methods can be regulated at the any time of autonomous navigation & exploration and the timer is placed in order to track the simulation time.

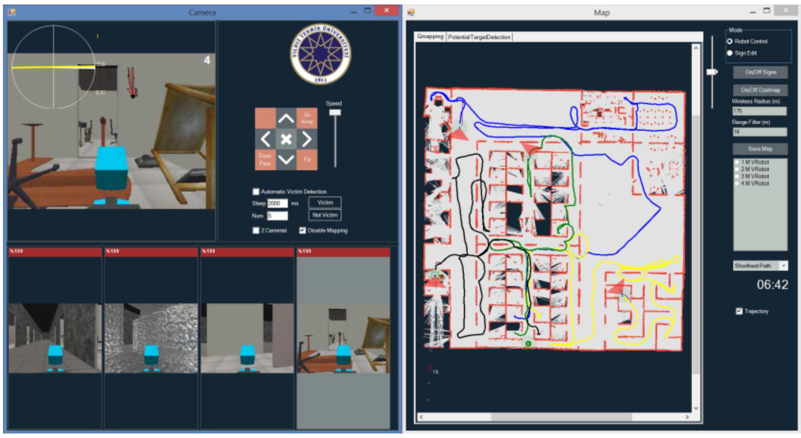

Fig.1 User Interface (a) Form 1, (b) Form 2

4 Distributed SLAM Algorithm

Accurate pose estimation plays an important role in solution of simultaneous localization and mapping (SLAM) problem required for many robotic applications. Although there are numerous successful solutions to SLAM, they usually involve various assumptions about the environment or require certain sensor technologies. We used Gmapping method, which presented in [3, 4] uses Rao-Blackwellized particle filter (RBPF), together with scan matching technique to improve the pose information provided by odometry (INS) sensor. As a result, particles are positioned around the correct location and packed into a narrow area. The next location of a particle is randomly selected from a unimodal Gaussian distribution, represented by randomly generated samples, around the same particle.

Rao-Blackwellized Particle filter solution for SLAM calculates the joint posterior estimation $p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1})$ for the map m and the trajectory of the robot $x_{1:t} = x_1, x_2, .., x_t$. [5]. To be able to calculate this estimation, all past laser measurements

$z_{1:t} = z_1, z_2, .., z_t$ and the odometry values $u_{1:t-1} = u_1, u_2, .., u_{t-1}$ has to be known. Rao-Blackwellized Particle filter than uses the factorization given in Eq. (1) to calculate the joint posterior.

$$p(x_{1:t}, m \mid z_{1:t}, u_{1:t-1}) = p(m \mid x_{1:t}, z_{1:t}).p(x_{1:t} \mid z_{1:t}, u_{1:t-1}) \quad (1)$$

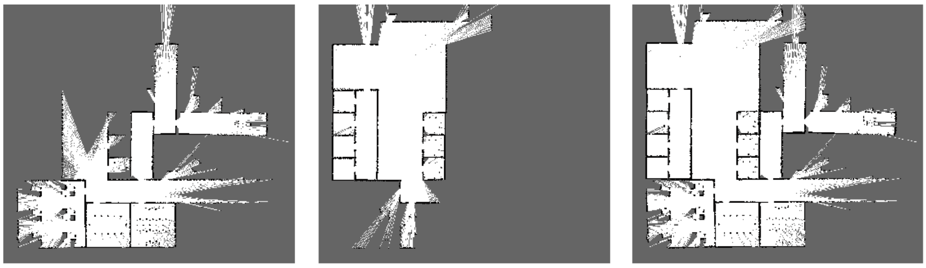

Fig. 2 Mapping with multi robots (a) Local map of Robot1 (b) Local map of Robot2 (c) Global map

$p(m \mid x_{1:t}, z_{1:t})$ is computed analytically and represents the map building process with known poses and laser measurements. The particle filter approach is used to calculate the $p(x_{1:t} \mid z_{1:t}, u_{1:t-1})$. Particle filter method generates random $x_t^{(i)}$ values, as many as the number of particles, to estimate $x_{1:t}$ values at each time stamp. An importance weight value $w_t^{(i)}$ is assigned to each particle depending on sensor measurements. Resampling process aims to increase the number of fittest particles while eliminating the less effective samples or particles.

As the variance of the odometry sensor increase, initial particles distribute over a larger space. As a result, more particles are required for convergence. Scan match based optimization which is described in [6], is used to improve the initial particle selection by providing particles to fall around different centers.

Original Gmapping method is proposed only for one robot. We implemented original Gmapping for each robots to obtain their local maps. Fig 2, a and b represent each robots local maps which constructs with original Gmapping. Each robot runs their local slam process and optimized their odometry locations. This process is called first level optimization. Optimized odometry location is also closer to the ground truth values. We implement multi robot Gmapping for comStation. This process is used first level optimized odometry that came from robots slam process, and optimized this value according to global map. This process is called second level optimization and this process outputs is also more closer to the ground truth. Fig.2c represents the global map, which is construct in comStation.

5 Victim Detection

Our previous victim detection algorithm was based on Histograms of oriented gradients (HoG) [7, 8]. Its true positive rate is very high. But its false positive rate is also very high. So it produces very frequently victim alarm signals. These disturbing signals take the operator's time.

Algorithms based on HoG are highly accurate against object categories that have a sufficiently static shape. But they are incapable of recognizing the targets having highly articulated figures such as human beings which are the main case of search and rescue missions.

In literature, deformable partial maps (DPM) [9] were presented to identify highly articulated figures. We created a dataset to test the performance of DPM. In the USARSim environment, the subjects have a wide range of variations in pose, appearance, illumination and background. Moreover, the approach angle of the robot to the subject creates lots of variations. During the creation of the dataset, these situations had been considered. Our current database contains 331 negative (non-victim) and 456 positive (victim) images. 49 positive and 50 negative images were used as our test set. In DPM, the default model was generated with real images. So, the default model could not detect our simulation victims. When we generate the DPM model with our simulation dataset, we achieved very good victim detection ratios (TP=96%, TN=94%, FP=%4, FN=%6). In Figure 3, some positive test images are given.

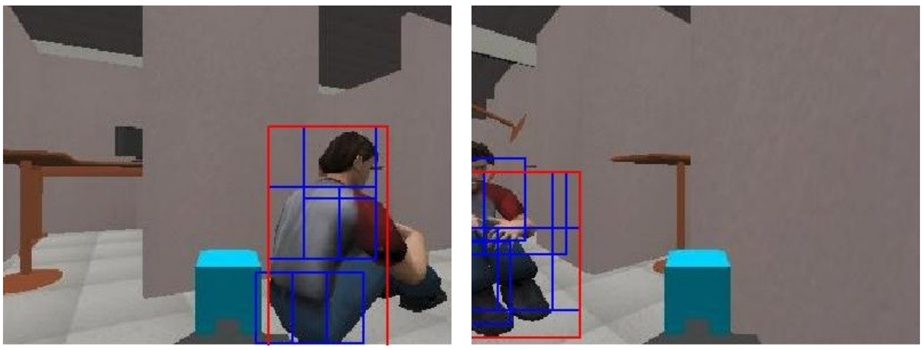

Fig. 3 Some positive test images

Besides its high identification performance, DPM model also provides the victim area in the images. In Figure 3, the blue squares show the victim parts, the red squares show the victim. But, DPM model requires more computational resources than our previous HoG based model. It takes about 5 seconds for each frame. We are trying to find ways to decrease its computational cost.

6 Multi Robot Exploration

Our autonomous exploration strategy is based on finding the frontiers having the most potential. A frontier is defined as an area consists of connected grids having unexplored neighbor grids. The potential of a frontier is calculated according to Eq(2).

$$p(F,R)=A(F) / distA(F,R) \tag{2}$$

In Eq.2, F is the frontier, R is the robot, A(F) is the area of the F, distA(F,R) is the length of the minimum path between F and R. distA(F,R) is calculated with A* algorithm. A frontier having the biggest p(F,R) value is selected as the goal.

When we have multi robot, a robot-frontier matching method should be applied. We decided to use the method proposed in [10]. The computational load of distA(F,R) is very high in multiple robot scenarios. In [10], distE (Euclidean distance) was proposed instead of distA in the early steps of matching algorithm. It also proposes a matching algorithm without searching all possible matches.

In the media restricted area some additional modules should be initiated in order to provide best exploration and navigation pattern. Central based processes are lost their efficiency in media restricted areas because there is a possibility to lose the contact of any robot and any moment during the exploration so each of the robot should decide the best movements themselves. According to this environment primarily, robot is navigated autonomously to the outside of the media limits as soon as the target points which is assigned from target selection process, are received from communication base. Robot has been stand on the received path in spite of the fact that robot reaches the media limit. In that time, environment information is started to collect and stored where is showed in Figure 4. Secondly, the robot is navigated towards to each of its targets in this way the disaster area is explored by the robot. Finally, robot has been driven to the inside of the media limits by the program when the data is enough and the exploration information is directed to communication base. Communication base reconstructs the global map with new exploration data which is received from the robot (Figure 5).

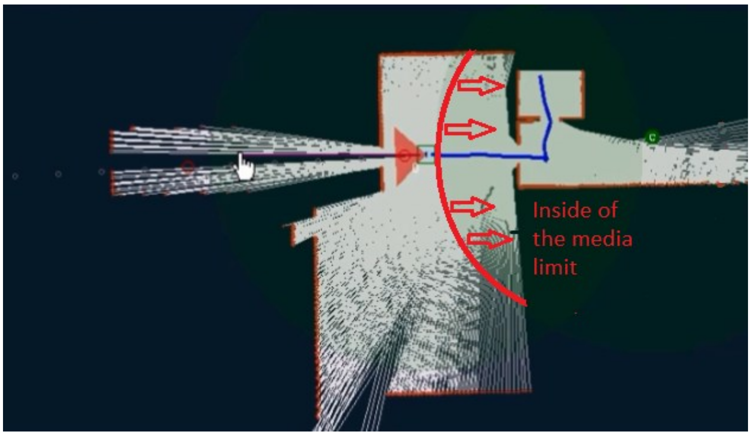

Fig. 4 Exploration in out of the media limits

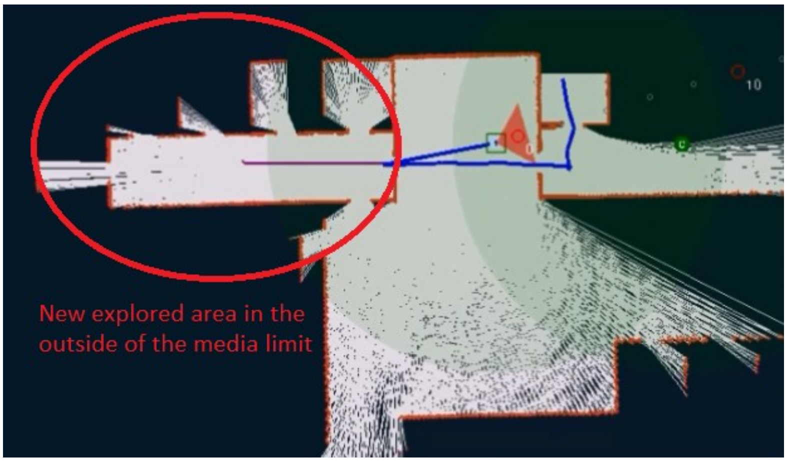

Fig. 5 Exploration in out of the media limits

7 Conclusion

In this paper, we give an overview of what our team developed for this year. We concentrated to the developing of our distributed SLAM algorithm, victim detection, and multi robot exploration techniques. The experience we gain from virtual robot competition will allow us to improve algorithms for our real robots.

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