Amsterdam Oxford Joint Rescue Forces
Team Description Paper
Virtual Robot competition
Rescue Simulation League
RoboCup 2011

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Abstract. With the progress made in active exploration, the robots of the Joint Rescue Forces are capable of making deliberative decisions about the distribution of exploration locations over the team. Experiments have been done which include information exchange between team-members at rendez-vous points and dynamic role switching between relays and explorers. In the previous competition exploration was demonstrated with large robots with advanced mobility, such as the Kenaf and the AirRobot. This year our mapping algorithms are extended to be able to explore with the smaller AR.Drone, a flying robot used in the International Micro Air Vehicle competition. Further, progress will be demonstrated in automatic victim detection.

Introduction

The RoboCup Rescue competitions provide benchmarks for evaluating robot platforms' usability in disaster mitigation. Research groups should demonstrate their ability to deploy a team of robots that explore a devastated area and locate victims. The Virtual Robots competition, part of the Rescue Simulation League, is a platform to experiment with multi-robot algorithms for robot systems with advanced sensory and mobility capabilities.

The shared interest in the application of machine learning techniques to multi-robot settings [1] has led to a joint effort between the laboratories of Oxford and Amsterdam. This year machine learning techniques are used to advance the perception and Simultaneous Localization And Mapping (SLAM) capabilities of our team. For this year's challenge the automatic victim detection is of major importance, although the quality of the map becomes important to coordinate the efforts in larger robot teams.

1 Team Members

UsarCommander was originally developed by Bayu Slamet and all other contributions have been integrated into this framework. Many other team members [2–6] have contributed to perception and control algorithms inside this framework. In advance of the Iran Open this year several improvements in the user interface have been made. A separate socket connection was created to broadcast the camera images, which improved the response time on drive commands. The drive commands can also be given with keyboard and pointers on the map. The latter option was coupled with a new behavior: way-point navigation.

The following contributions have been made this year:

Nick Dijkshoorn	: smoke and fire simulation [7], 2.5D SLAM, communication
Helen Flynn	: object recognition with weak classifiers [8]
Okke Formsma	: smoke and fire simulation [7], on-demand SLAM
Sander van Noort	: smoke and fire simulation [7], Nao model
Carsten van Weelden	: AR.Drone model
Chaim Bastiaan	: victim behaviors [9]
Niels Out	: radar sensor [10]
Olaf Zwennes	: automatic map generation
Seváztian Soffia Otárola	: webbased user interface
Julian de Hoog &	: multi-robot exploration[11], communication roles [12]
Stephen Cameron	
Arnoud Visser	: autonomous exploration [11, 12]

2 2.5D Simultaneous Localization And Mapping

One of the most fundamental problems in robotics is the Simultaneous Localization And Mapping problem (SLAM). This problem arises when the robot does not have access to a map of the environment and does not know its own pose. In SLAM, the robot acquires a map of its environment while simultaneously localizing itself relative to the map. This knowledge is critical for robots to operate autonomously. SLAM is an active research area in robotics. A variety of solutions have been developed. Most solutions rely on bulky sensors that have a high range and accuracy (e.g., SICK laser range finder). However, these bulky sensors cannot be used on small (flying) vehicles. As a result, researchers focused on using vision sensors. Vision seems to offer a good balance in terms of weight, accuracy and power consumption. Lightweight cameras are especially attractive for small flying vehicles (AUVs), which are less affected by obstacles. Steder *et al.* [13] addresses the SLAM problem using an AUV with two low-cost down-looking cameras in combination with an altitude sensor. Their approach is able to learn visual elevations maps of the ground. If the vehicle carries only one camera, a visual map without elevation information is generated. Caballero *et al.* [14] present an approach that uses monocular vision. Inter-motions are used to estimate the motion of the AUV. Online mosaicking is applied to reduce the impact of accumulative errors in the position estimation.

Our research addresses the problem of creating visual elevation maps of the ground using only a single camera (monocular vision) and an ultrasound sensor. Experiments are performed using the Parrot AR.Drone quadrotor helicopter. This helicopter is equipped with a low-resolution down-looking camera, an ultrasound sensor and an inertial unit that measures pitch, roll, yaw and accelerations along all axes. The vehicle is controlled by sending commands over a Wi-Fi connection. As described in section 4.2, a model of such an AR.Drone quadrotor is available in USARsim.

The map and pose of the vehicle are estimated using the measurements obtained by vehicle and the controls that are executed by the vehicle. However, sensors are noisy and the control commands are not executed accurately. This introduces uncertainty and makes the SLAM problem difficult. Probabilistic approaches are used to represent uncertainty explicitly. By doing so, they can represent ambiguity and degree of belief in a mathematically sound way. A possible probabilistic approach is to use an Extended Kalman Filter (EKF). Mosaicking is applied to reduce the impact of accumulative errors. The mosaic consists of a network of inter-image relations and is used to create a consistent view of the environment. This mosaic is used as a resource to detect drift in position estimations. Results of this method are given in Fig. 1. Both for the simulated and real AR.Drone a visual map is created with enough quality for human navigation purposes. The camera images in simulation are postprocessed (decreased saturation, increased brightness, downsampled resolution) to mimic the real images. Our current hypothesis is that the remaining stitching errors for the real AR.Drone are due to the effect of automatic white balancing of the camera. These small estimation errors should be easily corrected by implicit loop closure in more advanced SLAM algorithms.

(a) simulated   (b) real AR.Drone
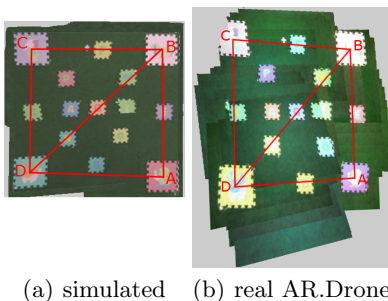
Fig. 1. Visual map of 1.5x1.5m created by a Parrot AR.Drone quadrotor with a map stitching method. The AR.Drone was flying at respectively 0.80 and 0.85cm

The mosaicking method assumes that the terrain is approximately flat, which does not hold when flying at low altitude. The parallax effect results in faulty image transformations and an inconsistent mosaic. Our method to prevent the parallax effect is by removing (masking) all obstacles from the camera frames,

such that a flat terrain remains. The ultrasound sensor is used to create an elevation map of the environment. The resulting elevation map is fused with the mosaic to obtain a visual elevation map. This same elevation map is used to find obstacles and mask parts of the camera frames that correspond with obstacles.

The final application will fully autonomously create a visual elevation map of the environment. The resulting map is generated in real-time and is displayed on a screen. The current pose of the vehicle is marked on this map. The user interface can be used to guide the vehicle to specific (unexplored) areas of map.

3   Victim Detection

This year we are using a combination of Viola and Jones' face detection algorithm[15] and skin-color histograms in order to detect victims. By employing this dual approach to victim detection we hope to reduce the false positive rate which has been a hindrance in the past. Viola and Jones' detector is based on Haar features and the AdaBoost boosting algorithm. AdaBoost is a well-known algorithm for generating strong classifiers from many weak ones. The weak classifiers used in Viola and Jones' detector are based on Haar features of three kinds: a two-rectangle feature is the difference between the sum of the values of two adjacent rectangular windows. A three-rectangle feature considers three adjacent rectangles and computes the difference between the sum of pixels in the extreme rectangles and the sum of the pixels in the middle rectangle. A four-rectangle feature considers a 2x2 set of rectangles and computes the difference between sums of pixels in the rectangles that constitute the main on and off-diagonals. For a 24x24 pixel sub window there are more than 180,000 potential features. The task of the AdaBoost algorithm is to pick a few hundred of these features and assign weights to each using a set of training images. Object detection is then reduced to computing the weighted sum of the chosen rectangle features and applying a threshold. This is a very fast operation. We trained various classifiers for faces in both upright and lying down positions, using images from Usarsim [16].

In the past we have found [8] that the Viola - Jones detector has quite a high false positive rate (that is, if incorrectly classifies regions of an image as a face). This year we are combining the detector with a colour-based skin detector in order to reduce the rate of false positives. The skin detector is based on a histogram of skin color used in the 2007 Virtual Robot Competition[3]. A 3D colour histogram is constructed in which discrete probability distributions are learned. Given skin and non-skin histograms based on training sets it is possible to compute the probability that a given colour belongs to the skin and non-skin classes. Using this classifier we can discard large parts of the image as containing victims. We then run the Viola - Jones detector over the reduced image search space.

4 Infrastructure Contribution

The Amsterdam Oxford Joint Rescue Forces will also this year contribute on several aspects of the competition environment. The contributions of previous year (Battery, ComServer interface, Fire and Smoke, Kenaf) are indicated in [17].

4.1 Automatic map generator

One of the contributions this year will be an extension of the automatic map generator currently available in USARsim. The map generator will be extended in such a way that the difficulty of the environment can be gradually increased. Difficulty can be expressed along several aspects, such as indicated in the apriori information of previous competitions (mobility, communication, victims). This time the focus will be on another aspect, the difficulty to map the environment.

Another aspect is the development of robots with other means of locomotion than wheels (to circumvent the current problems with wheeled robots in the UT3 simulator). One robot will be a quadrotor, the other robot will be a walking robot.

4.2 AR.Drone quadrotor

Our choice for the quadrotor is a Parrot AR.Drone, a robot the Universiteit van Amsterdam will use in the International Micro Air Vehicle Flight competition.
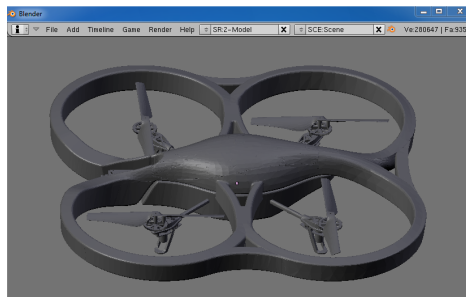
**Fig. 2.** 3D model of the Parrot AR.Drone helicopter

Before a model of such quadrotor can be implemented, insight in the dynamics is needed. A number of experiments have been designed, starting from a simple hovering and linear forward movements (see Fig. 3), towards more complex square trajectories.

The result of these experiments is a model for hovering (quite stable when enough texture visible on the ground), resulting in an absolute mean error of 7cm. The model for the linear motion is a relation between the control signal,

(a) Hovering   (b) Forward motion
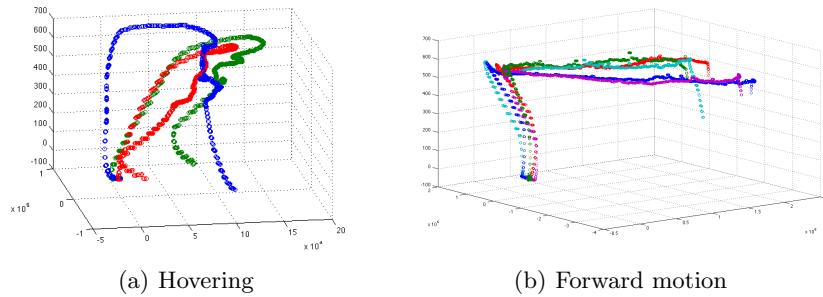
Fig. 3. The trajectory of a Parrot AR.Drone helicopter during experiments

the pitch angle and velocity. Fig. 4(a) shows the result of every time a longer control pulse with a range of control signals (from 0.05 to 0.25 of the maximum pitch angle).

(a) range of signals strengths   (b) comparison real versus simulated
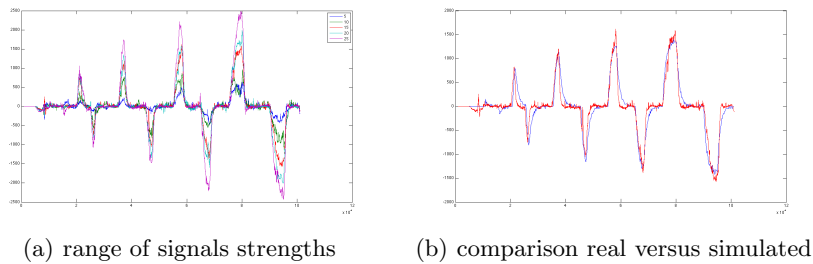
Fig. 4. The velocity for a sequence of positive and negative control pulses

The result of this model resembles the behavior of the real AR.Drone quite well. Fig. 4(b) shows the velocity of the real and simulated AR.Drone for the same sequence of control pulses.

4.3 Nao humanoid robot

A whole new development is a model of a legged robot. Here a model of an Aldebaran Nao robot is chosen. Originally a version with two joints (T2) was developed, which was gradually upgraded to a model with 21 joints (T21). The different parts are now nicely scaled, have their corresponding collision frame (see Fig. 5(a)) and are correctly linked. This implementation method (based on constraints) is fundamental different from the current implementation of the robot arms (based on Unreal's SkelControl objects), which do not simulate collisions well.

A remaining task is to initialize each joint correctly, and to find the correct constraints on each joint. For the joints in the head the behavior is already quite

(a) Collision frame   (b) Turning Head
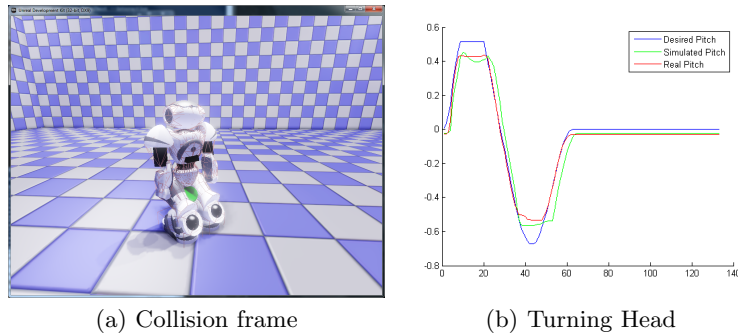
Fig. 5. An Aldebaran Nao robot

realistic (see Fig. 5(b)). Important for the joints' dynamic behaviors are the mass distribution, the inertia and the gravity. The green circle in Fig. 5(a) represents the center of mass of all body parts together. With the center of mass close to the hip, representing a mass distribution according to Aldebaran's specifications, the robot currently can stand and keep its balance. Even more complex behaviors as the Tai Chi dance can be executed without loosing balance, although here the dynamics still has to be fine tuned. In the near future the complexity of the tests will be increased, including the traversal on non-planar surfaces and across obstacles, as indicated in [18].

The development of those flying and walking robots will allow the development of many other walking and flying robots (based on the same principles).

5 Conclusion

This paper summarizes improvements in the algorithms of the Amsterdam Oxford Joint Rescue Team since RoboCup 2010 in Singapore. Many developments are not only valuable inside the Rescue Simulation League, but also valuable for the Standard Platform League and the Soccer Simulation League. For the Virtual Robot competition, developments in the user interface, victim detection and autonomy are important. Our progress as team on these topics was demonstrated at the RoboCup Iran Open 2011, where the 3rd prize was won.

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