The Keystone Fire Brigade 2003

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Abstract

The Keystone Fire Brigade is a robotic rescue team that has previously competed in competitions at Robocup (Fukuoka, 2002; Padua 2003), AAAI (Edmonton, 2002), and IJCAI (Acapulco, 2003). The key elements of our approach are an emphasis on vision, a fully autonomy solution, and an implementation on inexpensive robot bases. This paper describes the version of the team that competed at IJCAI in 2003. We overview the hardware employed, methods used for visual processing, map-making and victim identification. We also describe the experences we had in the test domain and offer some recommendations on future competitions.

Introduction

Robotic rescue is both a worthwhile application for artificial intelligence and a challenge problem that allows solutions to be compared in a controlled setting. Because of the extreme difficulty associated with the problem, most entries nowadays are teleoperated. This has been the case since the earliest rescue competitions, and the current competition at IJCAI was similar.

We believe that, ultimately, autonomous processing will be of great importance in robotic rescue. In rescue settings, issues such as operator fatigue, lack of situational awareness of the operator, cognitive load on the operator, and the number of individuals an operator can control in real time (Casper 2002; Casper & Murphy 2002) all place limitations on human control.

We also believe that a focus on autonomous processing is important from the standpoint of truly advancing artificial intelligence: the reason that most entries in the competitions are teleoperated is precisely because autonomous control is still very primitive in an areas as complex as robotic rescue, and avoiding the use of autonomous control mechanisms does not do anything to improve this technology. We believe that once autonomy has improved, teleoperation can be added to fill in the gaps where a human operator can be helpful to the situation without being overwhelmed. We have thus been focussing on autonomy as a key focal point in our work in robotic rescue.

This paper describes the Keystone Fire Brigade the University of Manitoba's entry in the AAAI Robotic Rescue Competition. Our approach embodies several principles we believe will ultimately be important in successful robotic rescue problems: autonomy, a multi-agent perspective, and parsimony.

Many problems are naturally amenable to solution through a collection of distributed agents. A multiagent approach to robotic rescue is a natural one: it is the approach that is already taken by humans in this problem; it allows the power of numbers to deal with the geographic distribution of the problem; and the presence of multiple agents allows any individual in this domain to be considered more expendable than would otherwise be the case. Because of this, we want to design agents that are meant to operate in groups.

Parsimony is an important goal in all robotics applications. Any additional feature has a cost, both financially and in terms of computing power and other local resources, and reliability. If a feature is not necessary to solve the problem, eliminating it provides more resources to those features that are necessary. We believe, like others (Balch & Arkin 1994) that the addition of any component should be carefully considered. Cost must be balanced with the efficacy of the equipment to the improvement of overall system performance. Parsimony is also one of the reasons that a multi-agent approach is important - by taking the same resources and spreading them among a number of simpler agents, the interaction of these over a geographic area can deal with the problem better than a single, highly complex agent. The more parsimonious the agent design, the more expendable any individual robot can be considered as well.

The remainder of this paper details the hardware platforms employed in this year's Keystone Fire Brigade the use of optical flow for localization and mapping, and discusses our experiences in this year's competition.

Description of the Robot Hardware

We have two primary motivations for hardware design in rescue robots. The first of these is reliance on ex-

Figure 1: Hummer: Robot platform using a Toy Car base

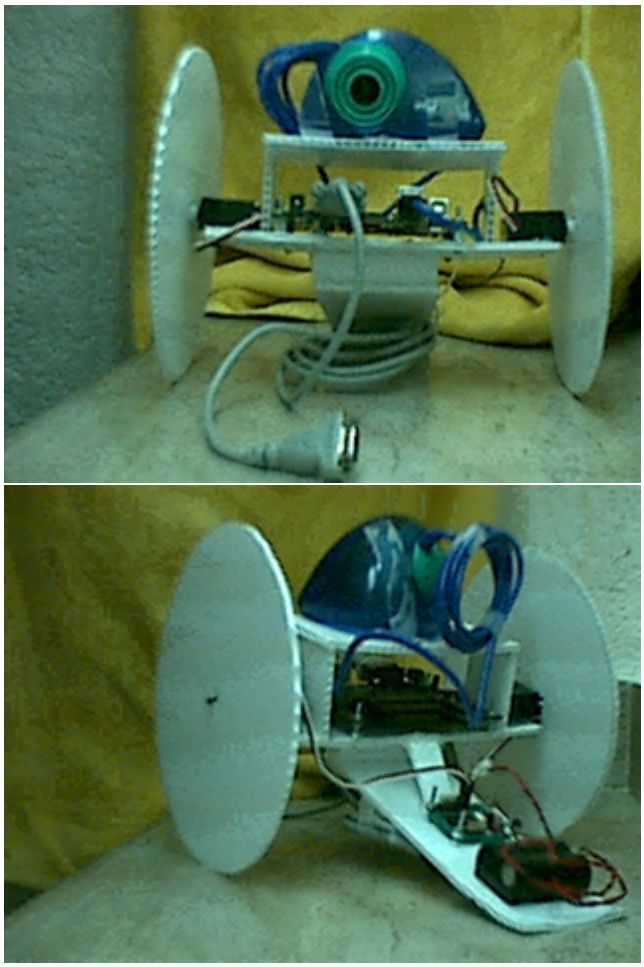
tremely simple robotic platforms. Ultimately, the task of robotic rescue will benefit from implementation on inexpensive platforms, since larger teams can be afforded and individual robots can be viewed as being expendable in a dangerous environment. Our motivation in using simple hardware, however, is to force reliance on more robust and versatile control methodologies. A system relying heavily on accurate odometry, for example, is severely crippled under conditions where odometry is inaccurate. A system that does not assume the availability of accurate odometry readings, however, will still operate under such conditions, as well as in conditions where odometry can be useful.

The second major design factor is an emphasis on vision. Each of our robots employs simple low-power CMOS cameras or webcams, and has enough local processing power for vision and robot control. Vision is the only sense employed by all of our robots.

In the 2003 version of the Keystone Fire Brigade the robots were based on two simple platform types. Figure 2 illustrates the first type, a small plastic remote controlled toy car (Hummer) from Nikko. While not possessing a true four wheel-drive, it affords a reasonably high ground clearance and stability over rough terrain. The hummer carries an Eyebot controller (Bräunl 1999), which consists of a 35 MHz 68332 processor with 2 MB of static RAM. The processing speed is very low by today's standards (supporting approximately 1 fps vision along with the processing necessary for autonomous control), but it is comparatively cheap and also supports a direct connection between a CMOS camera and the processor itself. Furthermore, the Eyebot controller provides the necessary interface to connect motors, servos, gyroscopes, and many other sensors directly to the controller.

Figure 1 illustrates our new base type, a custom design built from simple corrugated posterboard, with

Figure 2: Rescue2: Robot platform using a simple corrugated board base (front and rear views)



two servos attached to drive the left and right wheels, and an integrated webcam for vision. The servos were modified by cutting out the motion stop and thus provide relatively nice velocity control. The platform carries a much more powerful processer than the other base, a 300MHz Intel Xscale board, with 64MB RAM. This configuration is powerful enough to support autonomous control sofware along with 5 fps vision. In addition to these autonomous robots, we also deployed a teleoperated base (A PT cruiser approximately three times the size of the hummer depicted above), controlled via a small laptop with wireless Internet access. Our focus is mainly on autonomous control, but we wanted to take the opportunity to gather some experience with the some of the issues facing teleoperators in an environment such as RoboCup Rescue .

None of these bases would be suitable for real robotic rescue, mainly do to their fragile nature. However, they are sufficient to demonstrate the approaches we believe are useful for future robotic rescue work, and can navigate within the yellow zone of the NIST testbed (Jacoff, Messina, & Evans 2001). Our intent is to demonstrate the use of vision and autonomous control this task, and to further applied research in these areas in robotic rescue, rather than to tackle the less stable terrains in the orange and red arenas. In future, we intend to build more robust platforms employing the VIA mini-ITX board.

Visual Processing in the Rescue Domain

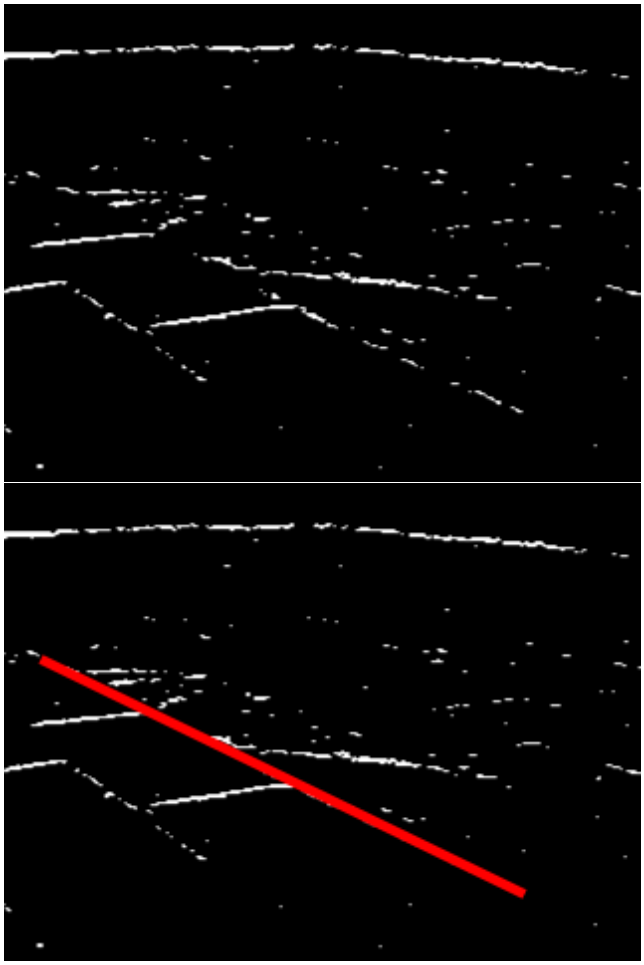
The greatest challenge on platforms such as those employed by the Keystone Fire Brigade is the design and implementation of pragmatic algorithms for intelligent visual processing, and the adaptation of these to the the low frame rates that are achievable using the embedded systems driving the robots.

The use of vision as the only form of sensing requires that vision not only be used to identify victims, which is the primary use of vision for most teams, but also to allow the robot to localize and map the environment. The following subsections describe our methods for dealing with each of these elements.

Ego Motion Estimation

In order for a robot using only vision to map an environment, its progress through the environment must be measured by vision rather than by odometry, sonar, laser, or a combination thereof. This is the problem of ego motion estimation, which requires the robot to estimate its movement in terms of distance and angle by examining the differences between visual frames. This is an extremely difficult problem, mainly because of the amount of confusing or conflicting information in visual frames. Furthermore, in the rescue environment itself, there is significantly less structure than that available in other common robotic environments. In soccer for example, the detection of walls can be done by plotting lines from the bottom of the image up to a white colour change (figure 3), and then calculating the wall's likely position based on the end points of the plotted lines (Baltes 2002). While some consideration has to be made for the portions of the wall that are not visible (i.e. obscured by the ball or other players), there is generally enough information in most frames to plot the wall's position quickly. In more general environments such as the rescue domain, however, the structure that can be assumed in simpler environments does not exist. Instead we must employ more sophisticated edge detection algorithms (upper part of Figure 4) followed by a line detection algorithm (Hough transform), illustrated in the lower part of Figure 4.

Figure 4: Detecting Lines in the Rescue Environment



While every recognized line in the rescue domain is not a wall, we can still employ these regular features to do ego-motion estimation. Our approach uses the optical flow between images to estimate the motion of the robot (Figure 5), and also to indicate a lack of motion on the part of the robot (i.e. detecting when the robot is stuck).

If a recognizable pattern (a set of lines, intersections

Figure 3: Detecting Walls in Soccer

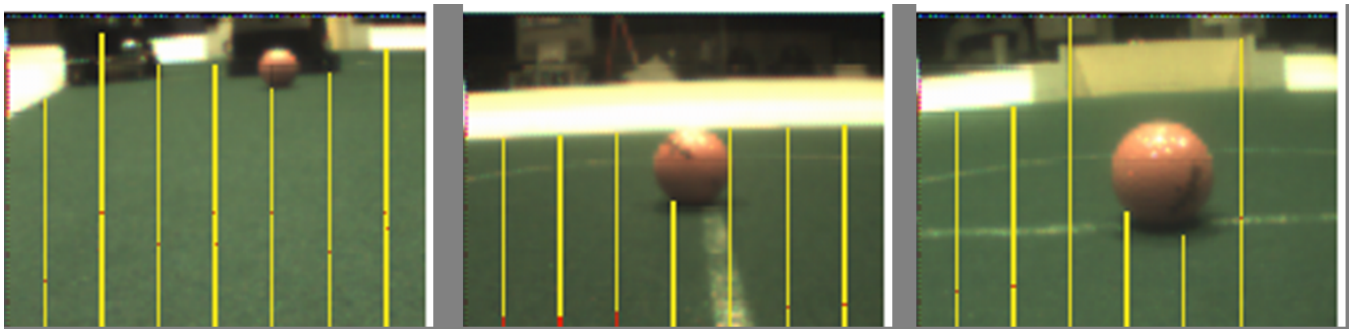
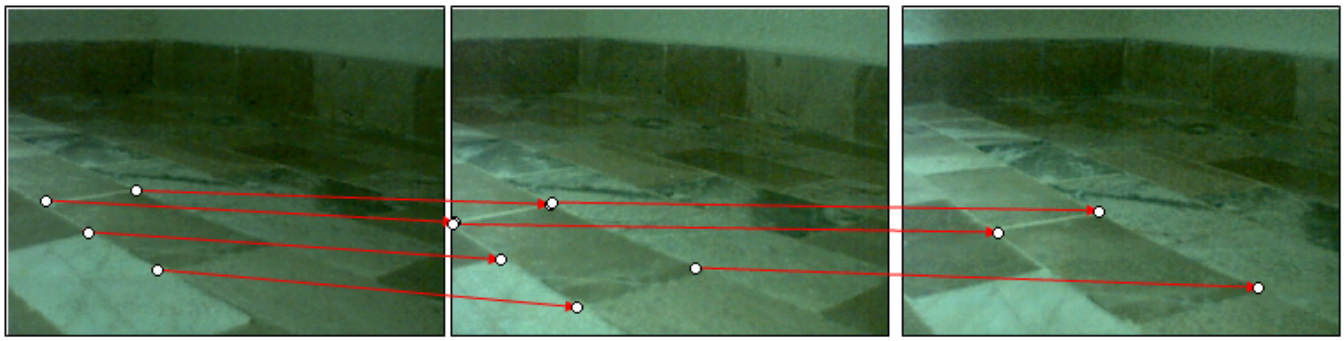


Figure 5: Ego Motion Detection from Visual Frames



between lines, etc.) can be recognized in two different frames, we can compute the change in angle and distance on the part of the robot that produced that change in visual reference point. Note that we assume that the line is at a constant height (e.g., a line on the floor).

Figure 6 shows the geometry of the situation. Assuming that the robot can determine the angle between itself and a line, then the change in orientation $\delta\theta$ can be easily computed by the difference in angle.

In the case of differential drive robot, this allows one to calculate the *difference* between the right and legft wheel velocities (assuming the width of the robot is known). In the case of a rear-wheel or front wheel drive car, the steering angle can be computed (assuming the axle distance of the robot is known).

The change in angle of the line does not allow one to solve for right and left wheel velocities (in the case of a differential drive robot), or the linear velocity (in case of a car-like robot). However, given that the robot can also determine the distance between the robot and the wall, solutions to the kinematic equations can be found and the motion can be recovered. The geometry and solution is shown in Fig. 7.

To determine if the robot is blocked or otherwise stuck in one position, the image is broken up into 16 equal sized sub-images. Of these, only the bottom 8 sub-images need to be considered - everything else is

Figure 6: Determining the change in angle from two visual reference points

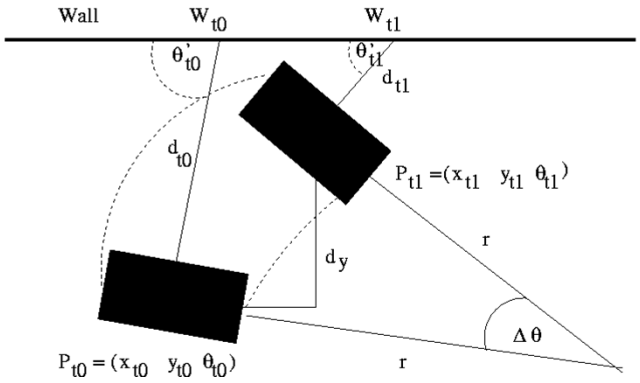
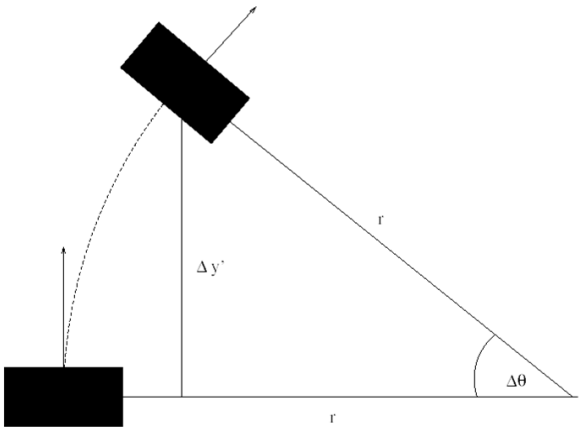


Figure 7: Determining the distance travelled from two visual reference points



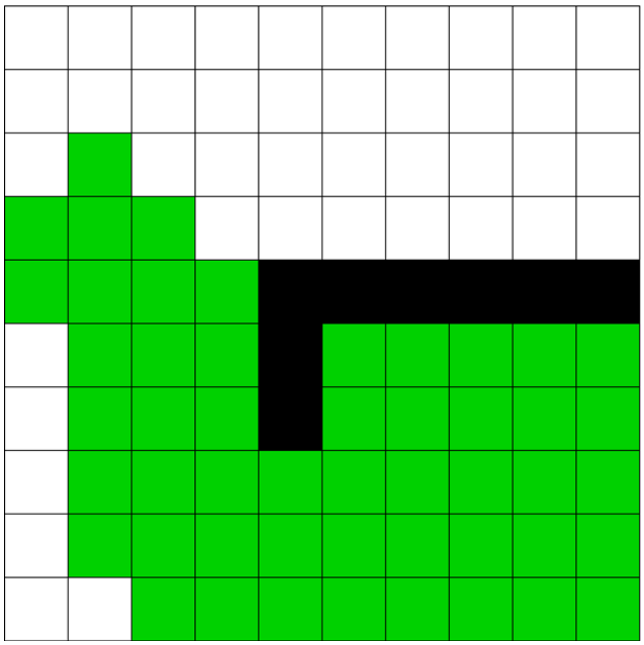
further away and would not be likely to provide useful feedback regarding the motion of the robot. The system then computes the differences between the current and the previous image for each quadrant. The colour difference is defined as the sum of the absolute value of the differences in the red, green, and blue channels. If the difference in a sub-image is above a threshold, the quadrant is marked. If there are more than eight marked sub-images and the motors were turned on in the previous time step, than the system signals that the robot is stuck or blocked. We break the image into sub-images to allow for localized changes due to the motion of some other agent or other external motion in the image, to try to limit the number of false positives.

Simultaneous Localization and Mapping (SLAM)

Just as we rely solely on vision for localization through ego-motion detection, we also rely on vision for constructing a map while loczalizing through optical through. This results in a chicken-and-egg problem: While localization becomes easier as maps are created, we must begin out of necessity with no valid initial map, making localization difficult, which in turn complicates the process of constructing an accurate map.

Our approach to building a map involves the construction of sets of local two-dimensional maps. The robot makes a map of the immediate area around itself (1m x 1m), storing the map as an occupancy grid such as that shown in Figure 8. In this map, the robot has plotted an obstacle (in black) and an open area (in green), while the white areas represent unexplored areas. These local maps are separated by longer traversals (a random walk in a particular direction) and are linked together as topological maps. The distance and length of a traversal serves as a link between maps, but as new features are detected earlier maps are studied for these features, allowing local maps to overlap. The

Figure 8: Local Map



smaller size of the local maps allows the local area to be explored quickly, and the traversals between allow the robot to map different areas without errors in one map compounding to cause problems in later maps.

We plan in the future to extend this work to include a case-based reasoning system that employs typical sensor readings (especially "typical" images of the area) to identify areas and to connect them via topologial paths.

Detection of Victims

While the system for awarding points is strongly oriented toward the use of multiple forms of sensing, most victims in the NIST testbed are reasonably easily identified visually. While there is much current work on the visual detection of victims, we are attempting to work with a reasonably simple, pragmatic approach to this difficult problem.

Our victim detection approach uses both colour as well as shape information. Flesh colored spots are marked as possible victim locations (these algorithms were trained beforehand on flesh patches of team members in the lighting used in the test arena).

We have developed a 12 parameter colour model which uses Red, Green, and Blue as well as three difference channels: Red - Green, Red - Blue, and Green - Blue. The differences are included in this parameter model because of their tendency to remain relatively constant in different views of objects of the same colour despite of lighting variations over a field. This approach is the same used in our Doraemon vision server (Anderson & Baltes 2002) and has proven itself in years of robotic soccer competition.

Currently, we use a simple blob detection scheme. The system signals that it has found a victim by calculating the apparent size and aspect ratio of a skin coloured blob. If these parameters are within limits, the system signals the detection of the victim by performing a series of 360 degree turns at the current location. It then continues to search the environment.

Discussion

This was our second year in the competition, and we were frustrated by a number of hardware failures. More robust platforms are required even to successfully operate in the Yellow arena of the NIST testbed, and we intend to develop a harder-wearing platform (with the same goal of parsimonious construction that has characterized our work to date).

Beyond the issue of hardware failures, the methods we are using resulted in low scores in general. While we intend to make every effort to improve the performance of our team for next year, performance using these techniques will continue to be poor in the foreseeable future: ego-motion estimation and mapping through the analysis of optical flow in a domain such as robotic rescue are both extremely hard problems, and we do not expect perfect solutions to these problems to magically appear. However, furthering work toward the solution of hard problems such as these is one of the goals of rescue competitions. For next year, we intend to work on improving the frame rate, which should result in corresponding improvements in mapping and localization. We also intend to modify our algorithms to focus more computational effort on those parts of the image that are likely the most important: in front of the robot and at the horizon.

Our experiences this year and last have led us to make a number of recommendations for future competitions. First, in both the IJCAI and Robocup competitions, it was evident that the multiplier currently included for the use of multiple sensing methodologies has too strong a weight. It is too easy for a teleoperated team using multiple forms of sensing to discover a victim visually (i.e. victim detection is essentially complete at that point), and then simply employ one sensor after another in the same position to receive additional points for work that was already performed once using the operator's vision. This is analogous to the kind of activity that took place last year when there was a multiplier for multiple robots, and serves as a similar argument to removing this multiplier as well. Multiple sensory approaches should allow robots to find *more* victims, not gain additional points from the same victim. The tags that were used to label victims were an interesting variation on previous competitions, and the use of these did provide some incentive to explore the area around victims further after visually identifying them. Rules should also be flexible enough to allow for fully autonomous approaches to have some chance at competing. Revising the rules committee, which has been inactive for some time, would be helpful in dealing with these and other issues.

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