

RoboMutts

Robert Sim, Paul Russo, Andrew Graham, Andrew Blair
Nick Barnes & Alan Blair

Dept. of Computer Science & Software Engineering
The University of Melbourne
3010, Australia
{nmb,blair}@cs.mu.oz.au

1 Introduction

A software control system for an autonomous mobile robot must be capable of performing many complex processing tasks in real time. Such tasks may include localising within the environment, recognising objects or safely avoiding static and dynamic obstacles. The focus for our team this year was to build a solid structural base, to be used in future RoboCup competitions. This led us to concentrate on development of effective reusable components such as a robust vision system. The RoboMutts team was a joint venture between the University of Melbourne and RMIT University. This paper focuses on the parts of the system developed at the University of Melbourne.

2 Team Development

Team Leaders: (University of Melbourne) Dr. Nick Barnes & Dr. Alan Blair

Team Members: (University of Melbourne)

Robert Sim, Paul Russo, Andrew Graham & Andrew Blair

– Mechatronics Students (Principal Development Team)

Gavin Baker, David Shaw

– Computer Science Students (Peripheral Development)

Team Leaders: (RMIT University) Assoc. Prof. Lin Padgham

Team Members: (RMIT University)

Simon Duff, Indra Indra, Christian Guttman

– Computer Science Students (Goalie Development)

Web page: <http://www.cs.mu.oz.au/robocup/dogs/>

3 Architecture

Our system model, although based around the Aibo robot, could in principle be applied to other hardware; the simple interfaces between modules means that it is straightforward to abstract away from the hardware level. The system is broken into four modules.

The *Visual Perception* module is responsible for obtaining data describing the world. In this implementation, data is extracted from the robot's digital camera and range-finder. It passes information to the *Body Perception* module which contains the relative positions of unidentified objects in a sensor centred coordinate system. The *Body Perception* module observes the internal state of the robot, including battery level, temperature, gyroscope and joint angles. This module combines information about internal state with visual information to identify visible objects, and express their relative positions in a robot-centred coordinate system. The *Knowledge Representation* module uses the data provided by the *Body Perception* module to maintain a database on all objects in the world, as well as localising with respect to the world. Finally, the *Planning & Execution* module consults the *Body Perception* database for information to construct plans of action. The following sections outline the implementation of our system.

4 Vision

Colour calibration: In the Sony Legged League, surfaces can be uniquely identified by applying labels to colour regions within the spectrum. Hence, colour calibration is required to precisely define colour regions in YUV.

To gain the required information about the YUV colour space, a large set of images which contained colours of interest were collected prior to runtime. To ensure that each colour was well represented, several images of each colour were collected, in different lighting conditions, with different camera offsets. Desired regions of colour were extracted from each image to yield the colour map in UV shown in Figure 1(a).

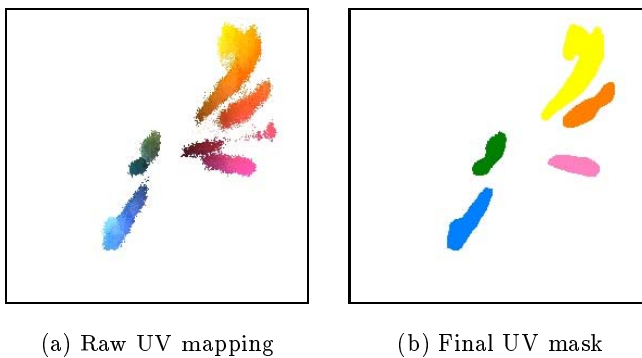


Fig. 1. Creation of the UV colour mask

Image segmentation: Our team has developed a representation that is fast and space efficient. The 3-dimensional YUV space is collapsed down into the UV plane by discarding the Y values. As there is separation between all colours in this representation, it is sufficient to neglect the Y values. By defining the *colour mask* in the UV plane (see Figure 1), segmentation was performed in a manner that is more accurate than the standard hardware segmentation in which a series of cubes is used to define colour regions. Only using U and V is forgiving of the lighting conditions, since different lighting levels affect the Y component more than U and V. Once segmented, a connected components routine is carried out on the images to identify *regions* of colour. Figure 2 demonstrates the result of performing segmentation using the colour map technique.

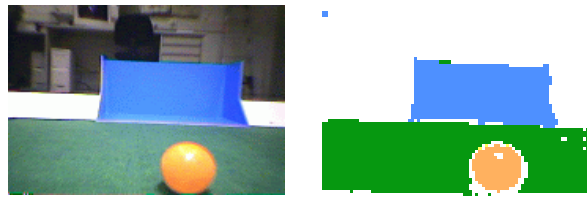


Fig. 2. Actual captured image before and after segmentation.

Object recognition: Objects in the image need to be identified based on colour, shape and position relative to other colours. We developed a set of heuristics for the competition, designed to optimise the trade-off between *false positives* (objects falsely identified) and *false negatives* (observed objects not being identified). False negatives waste computation, as the images are processed, but no useful information is extracted. False positives cause havoc with future calculations relying on the data. Our heuristics are of the form: *if an orange pixel joins a green pixel, the object is the soccer ball*. The use of such heuristics facilitate identification based on connected regions of colour leading to robust, reliable object detection.

5 Localisation

We developed a passive localisation system. *Passive* localisation refers to the process of localising without explicitly looking for landmarks. It is based on the notion that landmarks will come into view when the robot is moving around, or looking for objects, such as the soccer ball in RoboCup.

We adopted a triangulation algorithm to determine the robot's position. Triangulation differs to trilateration in that it uses distances *and* angles to landmarks to calculate position, instead of just distances. This means that position can be uniquely determined by two landmarks, instead of three with trilateration [See [NSPK99] for a trilateration implementation]. In our implementation, we

chose the two landmarks for which the relative position is known to the greatest confidence, according to a data history.

At times, the robot may be in a situation where every entry in the data history is unreliable, in which case it can't perform the localisation calculation. In these cases, odometric data is used to estimate the robot's position.

6 Behaviours

Perfect vision and localisation is of little use without the ability to make decisions based on the knowledge obtained. We implemented a state based decision making strategy that provided reactive, deterministic decision making. We identified a clear set of states for which different robot behaviours would be desirable. Transition between these states were reactive, based on the robot's perception. Reactive behaviour was desirable to ensure the robot was not carrying out a pre-computed plan no longer relevant in the dynamic soccer environment. Due to time restrictions Sony's MoNet was used for motor control.

7 Conclusion

We implemented a flexible framework allowing for further development in future RoboCup competitions. In particular, a robust vision system allowed our robots to see the ball when almost the full length of the field away.

The most obvious area in which further research could focus is development of custom motor control. In the area of vision, one significant improvement would be the incorporation of an edge detection routine, to assist in localisation. The localisation system also has avenues for further development in areas such as walking drift corrections. This could be done through improved odometry, or by some other means, such as using a single landmark to correct pose.

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References

- [NSPK99] Luis E. Navarro-Serment, Christiaan J. J. Paredis, and Pradeep K. Khosla. A beacon system for the localisation of distributed robotic teams. Technical report, The Robotics Institute, Carnegie Mellon University, 1999.