Real-Time Clustering Of Position And Omnivision Object Observations In The RoboCup Domain

Rob Janssen
Department of Mechanical Engineering
Eindhoven University of Technology
P.O. Box 513
5600 MB Eindhoven
The Netherlands
Email: R.J.M.Janssen@tue.nl

René van de Molengraft
Department of Mechanical Engineering
Eindhoven University of Technology
P.O. Box 513
5600 MB Eindhoven
The Netherlands
Email: M.J.G.v.d.Molengraft@tue.nl

1 Introduction

In the RoboCup Mid-Size league two teams of autonomous robots compete against each other in a game of soccer. One of the main issues, is for each robot to know where the peer and opponent players are located on the field. By using an omnivision camera the robot is able to obtain the position of robots in its own environment, but it cannot distinguish between peer or opponent robots. Another issue is that due to resolution deterioration of the camera on larger distances (>5m), the robot does not know what is beyond this range. By combining the peer position and omnivision object data from all peer robots and efficiently clustering this data a unique and complete view of the field can be created. This allows the robot for instance to plan a path over the total length of the field (>18m), or to pass a ball to a peer robot that is actually positioned beyond the robots own field of view.

2 Observation properties

The peer position and omnivision object data are send to the other peers by WiFi. These observations have several properties.

- the observations originate from moving robots on a 2D surface,
- the observations include noise,
- the observations are sequential in time,
- the actual number of robots present is unknown.

3 Clustering the data

To extract the relevant information from the observations an hypotheses-tree based sequential clustering algorithm [1] is adopted, with some adaptations to make it run in real-time and to deal with the dynamics of the moving robots. Labeling is added to distinct between peer or opponent robot and to track an identified opponent. If one of the originating observations contains a position measurement of a peer robot, the robot is labeled as ‘peer’. If the originating observations only contain position measurements obtained by the omnivision camera, the robot is labeled as ‘opponent’.

For each observation the following steps are performed.

1. the hypotheses tree is expanded. Either the new observation can be classified as clutter, a new observed robot or belonging to an already observed robot. If a new robot is observed it is labeled as peer or opponent,
2. a Kalman propagation is performed for each existing object in the hypotheses tree,
3. a likelihood update is applied, based on the spatial distance of the observation and the already observed robots,
4. the hypotheses tree is pruned so that it stays maintainable,
5. the hypothesis with the highest probability is selected.

The selected hypothesis describes the total number of peer and opponent robots. From the Kalman states that belong to these robots the current position and velocity of that specific robot can be derived. A static representation of the outcome of the algorithm is depicted in Fig. 1.

Figure 1: Observations (white), peers (blue) and opponents (red).

References