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Hypotheses based multi-object tracking in the RoboCup MidSize league

(Extended Abstract)

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ABSTRACT

One of the main challenges in the RoboCup MidSize league is to create a global view, or world model, of peer and opponent players in the game environment. This view is essential for strategic gameplay and global path planning. In this paper the team of TechUnited Eindhoven describes their solution to this issue. Ego and omnivision object measurements are shared amongst peer players. Each peer individually processes the measurements according to an hypotheses based sequential clustering algorithm. For each cluster Kalman observers are initiated from which an estimated position and velocity can be derived. This paper describes the first world model design known in the MidSize league that includes dynamics and labeling of peer and opponent players.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous

General Terms

Algorithms

Keywords

Collective intelligence, Mobile agents

1. INTRODUCTION

In the RoboCup MidSize league two teams of autonomous robots compete against each other in a game of soccer. By using an omnivision camera a robot can obtain the position of other robots in its nearby environment, but due to resolution deterioration this becomes difficult for objects positioned farther away ($>5\text{m}$). Another problem when using only omnivision information is that a robot can not visually distinct between peer and opponent players. To overcome these issues a global view must be created, in which all peer players share their available information of the objects in the field. In the RoboCup MidSize league this global view is referred to as a *world model*. With a world model it is for instance possible to plan a path from a defensive position straight to the opponent goal, or to pass a ball over large distances to a locally unobservable peer. In this paper the team of TechUnited Eindhoven explains the design and implementation of their world model. In this approach the ego and object measurements of all peer players are shared and

efficiently clustered such that for each object in the field, peer or opponent, a unique position and velocity is estimated. Other teams participating in the MidSize league have implemented a basic world model, from which only a rough estimate for the position can be obtained. The reigning world champion RFC Stuttgart uses a shared database for all agents [1]. In this implementation no data association between measurements is performed. An agent can simply access the information another agent has available. The Brainstormer tribots use a grid-based approach to determine overall occupancy on the field [2]. This approach lacks any form of tracking, and therefore no velocity estimates for opponent players are determined. The team of Cambada has implemented a more advanced method [3]. In this method a shared database can be accessed, in which a basic form of outlier-based clustering is performed.

The world model of TechUnited is an hypotheses based sequential clustering algorithm that clusters ego and omnivision object measurements into an a priori unknown number of dynamic objects. Basically, it is a Bayesian filter in which the state space grows with each new measurement. Each state describes a hypothesis of possible associations between measurements and clustered objects. Updating of the hypotheses probabilities is done by evaluating the metric distances between measurement and associating objects. To cope with dynamics, Kalman observers are initiated for every new observed cluster. Clustering data usually requires to know the actual number of clusters up-front [4], or to perform several trials while evaluating the rate of change using for instance the L method [5]. The described method in this paper is based on the work of Schubert and Sidenbladh [6], where the actual number of originating objects is supposed to be unknown. In their approach only static objects were considered. The approach described in this paper also includes the dynamics involved in the RoboCup environment, together with an addition that labels an observed object as peer or opponent.

2. METHOD DESCRIPTION

The measurements of all peer players are shared through WiFi. The measurements that each peer shares include a global ego-position and the global position estimates of objects that the peer observes through its omnivision camera. Each shared measurement holds a timestamp, by which the

measurements are sorted in time before they are sequentially processed. A label is added to the measurement, to classify a clustered object as either peer or opponent. For each measurement the following steps are performed:

1) Expansion of the hypotheses tree

In Fig 1 the hypotheses tree is visualized, where each new level describes the growing state space. For each measure-

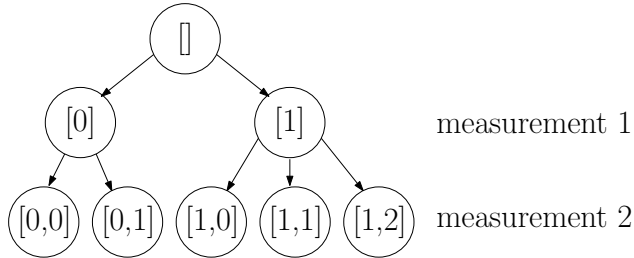


Figure 1: Expansion of the hypotheses tree.

ment a new level in the hypotheses tree is appended. When processing the first measurement two new hypotheses are created. Either the first measurement can be classified as clutter ([0]), or it can associate with a new observed object ([1]).

When the second measurement is processed the discrete state-space grows to five possible hypotheses. The circle with ([0,1]) describes the hypothesis that the first measurement was clutter and the second measurement associates to a new object. The circle with ([1,2]) describes the hypothesis that the first measurement associates to a first object and the second measurement associates to a second object, etc...

2) Inheritance of attached label

The object measurements obtained through the omnivision camera are labeled zero and the ego-position measurements are labeled X, the peer's ID number (1,2..6). If an observed object associated with a measurement labeled X, the observed object is labeled as peer X. If all associating measurements of a clustered object contained a zero-label, the object is labeled as opponent.

3) Object propagation

To cope with the dynamics of the moving objects, the objects are propagated during processing of a measurement. This propagation is done by initiating a Kalman filter for each object in the hypotheses tree. Each observed object is propagated according to the time interval between consecutive measurements. To minimize processing time a constant velocity model for the objects is assumed, and the Kalman gains are static and determined empirically. If the processed measurement associates with an observed object in the hypotheses tree, also a measurement update is performed.

4) Updating of hypotheses probabilities

The update for the hypothesis probability depends on the Gaussian distance from a measurement to an associating object. The closer a measurement is to an associating object, the larger the increase in hypothesis probability.

5) Pruning and normalization

The hypotheses tree is pruned and normalized to keep it maintainable. Pruning is performed by keeping only a fixed number of hypotheses that have the highest probabilities.

6) Selecting the best hypothesis

Selecting the best hypothesis is done according to the Maximum A Posteriori Estimate. The selected hypothesis contains the total number of peer and opponent players. From the associating Kalman filter the respective position and velocity of a player can be derived.

3. RESULTS

A static representation of the outcome of the algorithm is depicted in Fig. 2.

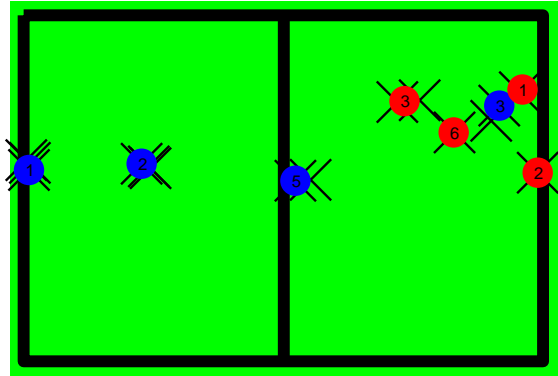


Figure 2: World model output semifinal 2010.

Measurements are indicated by crosses, peer players by blue dots and opponent players by red dots. An animated video that visualizes tracking performance can be found on <http://www.youtube.com/watch?v=7CXcilgU66Q>.

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