Team Description for Lucky Lübeck – Evidence-Based World State Estimation

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Abstract. This paper describes the important features of the team LUCKY LÜBECK Melbourne 2000 which is based on the MAINZ ROLLING BRAINS 1999 agent code. In LUCKY LÜBECK, a new method, *Evidence-based World state Estimation*, has been introduced, by which player and ball position can be estimated about an order of magnitude more accurately than before.

1 Introduction

This paper describes the entry of the team LUCKY LÜBECK to RoboCup 2000. LUCKY LÜBECK is based on data structures, functions, skills and player strategy from the RoboCup agent code developed by the first author together with his former team MAINZ ROLLING BRAINS during his time as their team leader [1–3]. Here we give an overview over the most important extensions of the former agent model.

A main aspect of the earlier efforts in [1] had been devoted to the development of a unified concept to represent world knowledge in a transparent way that would be consistent with both sensor readings and agent actions. LUCKY LÜBECK Melbourne 2000 extends this concept in a natural way for near-optimal reconstruction of agent and ball positions via a method which we call EWE (*E*vidence-based *W*orld state *E*stimation). In EWE, new evidence, e.g. sensor readings, is incorporated into the current world model striving to maintain a maximum degree of consistency. Instead of the simple, more-or-less plausible filtering heuristics used before, our new approach is clear-cut, conceptually concise and can be given a well-defined interpretation. The method is general and powerful and can be used in different contexts.

The EWE concept can be seen: 1. as a generalization of nonlinear Kalman filtering [4] towards model-based filtering; 2. as a world state description in terms of a generalized interval arithmetic; 3. as a natural extension of Markovian Self-Localization [5] to spaces other than 2-dimensional positions; 4. as a continuous implementation of BDI [6, 7] for world state estimation, since it strives at consistency between hypotheses about the world state and evidence.

2 Evidence-Based World State Estimation

In EWE, a single-valued state variable in the world model is replaced by a (multi-valued) set or a probability distribution of possible values for that variable. This multi-valued representation of the state variable models the agent's set of hypotheses about the true world state. Given such a multi-valued representation, the arrival of new evidence imposes restrictions on the set of possible and/or probable hypotheses, discarding some of them altogether and modifying the probability of others. For reasons of efficiency, in our agents we concentrated on implementing the EWE concept for the estimation of the most important world state variables, namely the position of the player and the movement of the ball.

Originally, the mechanism developed here was first used to determine ball position and velocity and later extended to also calculate the player position. For presentation purposes we will, however, first describe the calculation of the agent position, followed by the mechanism for ball localization. A first version of EWE was already implemented but not yet activated for Eurobocup Amsterdam 2000, since it was not sufficiently stable at that time. The first use of EWE in an official tournament was in the Melbourne 2000 event.

2.1 Determining the Agent Position

The agent position is a two-dimensional vector $p \in \mathbb{R}^2$. As corresponding multi-valued representation in our world model we use a two-dimensional polygon. This representation can be interpreted as a probability density distribution attaining the value $1/A$ in the inside the polygon and 0 outside (A being the area of the polygon). At the same time it forms the basis for a "polygon arithmetic" (a generalization of interval arithmetic to the 2-dimensional plane) which we will need later. Any real-valued quantity s sent to the agent by the server, be it angle or distance, is converted to a quantized value $\hat{s} = Q(s)$ via a *quantization function* $Q : \mathbb{R} \to \mathbb{R}$. The quantization functions used in the soccer server have the property that the *inverse quantization* $S := Q^{-1}(\hat{s})$ for any given value $\hat{s} \in \mathbb{R}$ is either an interval $[a, b] \subseteq \mathbb{R}$ or empty (if $\hat{s}$ can not result from quantization).

To determine its own position, our agent uses its neck angle, its body orientation and flag landmarks. From the raw neck angle $\hat{\phi}_{\text{neck}}$ as received by the agent, an interval $\Phi_{\text{neck}} = Q^{-1}(\hat{\phi}_{\text{neck}})$ of possible neck angles is computed. The orientation of the view cone is obtained from the observed angle of the field border lines, again yielding an interval Φ_{view}. Similar to arithmetic with single-valued variables, the angle interval for the agent orientation can be calculated to give $\Phi_{\text{orient}} = \Phi_{\text{view}} \oplus (-\Phi_{\text{neck}})$. The operator $-$ denotes inversion of an interval at the origin, reversing its orientation, and $\oplus$ is the convolution operation when interpreting the intervals as probability distributions; for the sake of simplicity, however, we implemented $\oplus$ not as convolution but as interval arithmetic $+$.

The landmark flag position data sent by the server give quantized values for distance and angle. Reconstruction via inverse quantization gives an interval for the possible true distances and one for the possible true angles of the flag. Given these, the set of possible relative flag positions can be reconstructed (sector in

Fig. 1 marked by solid line). The sector is then extended to the polygon marked by dashed lines to simplify further calculations. The same way the computation for Φ_{orient} traces the computation of a single-valued variable for orientation, appropriately rotating P_{flag} (taking into account the interval structure of Φ_{view}) and shifting the result w.r.t. the absolute flag position, we calculate a polygon area P_{player} of possible player positions. This process is repeated for every flag seen during the current time step. The true player position must be consistent with all of them. Therefore we compute the intersection of these regions (applying a probabilistic formalism would also be possible, but for sake of simplicity we selected a interval, or better, "polygon arithmetic" framework). An estimate for the position of the player is then obtained by averaging the corner positions of the intersection polygon. We found this polygon usually to be quite small and the resulting estimated positions to deviate around 5-10 cm from the true positions, which is more than an order of magnitude more accurate than the values obtained by conventional approaches.

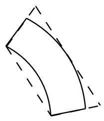

Fig. 1. Sector as defined by an orientation and distance interval

We are aware of the fact that CYBEROOS independently developed an approach similar to the one described in this section to estimate player position (private communication, Amsterdam 2000); so did the MAINZ ROLLING BRAINS (private communication, Melbourne 2000). To our knowledge, they restricted themselves to the calculation of the agent position.

2.2 Ball Position and Velocity Estimation

The generality of the EWE method allows us to determine ball movement in a conceptually similar fashion. Here, the approach of incorporating evidence needs to be applied to the phase instead of position space. To simplify the exposition, we limit ourselves to explain a situation where the player is placed at the origin of the coordinate system and looks along the x-axis and the ball is moving exclusively (and undisturbedly) along the x axis, the y-component of its movement vanishing. The equation of movement during a single time step for an undisturbed ball in the soccer server is given by

$$\begin{pmatrix} x(t+1) \\ v_x(t+1) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & \lambda \end{pmatrix} \begin{pmatrix} x(t) \\ v_x(t) \end{pmatrix} \tag{1}$$

where λ is the decay rate for the ball movement. The ball state is completely specified by the pair x, v_x. If the ball state is unknown at the initialization, the ball can be at any x-position inside the field and have any velocity $v_x \in [-v_x^{\max}, v_x^{\max}]$ where $v_x^{\max}]$ denotes the maximum speed. This uncertainty defines a rectangle in phase space. When ball information is observed, one obtains a distance (and an angle which vanishes in our example). This distance defines a distance interval, restricting the possible states in phase space to a rectangle relatively narrow compared to the a priori possible x-positions. The speed, however, is still unknown, i.e. the rectangle has still its full extent in v_x-direction. After one time step, the rectangle of expected possible states in phase space for $t+1$ becomes oblique due to Eq. (1). New evidence cuts a vertical slice from this rectangle; by virtue of its obliqueness, the feasible region in phase space is now much smaller, giving a much better defined value for velocity. In the following steps the size of the feasible region then quickly shrinks, greatly improving localization precision.

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