A Method for Incorporation of New Evidence to Improve World State Estimation

Martin Haker, André Meyer, Daniel Polani and Thomas Martinetz

Institut für Neuro- und Bioinformatik, Universität zu Lübeck
D-23569 Lübeck, Germany
polani@inb.mu-luebeck.de, martinetz@inb.mu-luebeck.de
http://www.inb.mu-luebeck.de/staff/{polani,martinetz}.html

Abstract. We describe an approach to incorporate new evidence into an existing world model. The method, *Evidence-based World state Estimation*, has been used in the RoboCup soccer simulation scenario to obtain a high precision estimate for player and ball position.

1 Introduction

One of the problems which agents in realistic multiagent scenarios are facing is the need for an adequate world model. Set in the context of the RoboCup soccer server, we describe an approach to reconstruct the true world state of an agent and of objects (here: the ball) sensed by it as closely as possible by incrementally incorporating new evidence. In this approach, *EWE* (*E*vidence-based *W*orld state *E*stimation), new evidence, e.g. sensor readings, is incorporated into the current world model striving to maintain a maximum degree of consistency.

EWE in many ways a natural approach for a near-optimal reconstruction of a world state. It is clear-cut, conceptually concise and can be given a well-defined interpretation. We believe it has a strong potential to be generalized to domains beyond the simulated RoboCup world. In fact, many important state reconstruction methods can be regarded as special case of EWE. The EWE concept acts: 1. as a generalization of nonlinear Kalman filtering (Lewis 1986) towards model-based filtering; 2. in a geometric context, as a world state description in terms of a generalized interval arithmetic; 3. as a natural extension of Markovian Self-Localization (Fox et al. 1999) to spaces beyond 2-dimensional spatial positions; 4. as a continuous implementation of BDI (Burkhard et al. 1998; Rao and Georgeff 1995) 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 is a model of the set of hypotheses that the agent carries about the true world state. The arrival of any new evidence imposes restrictions on the set of possible and/or probable hypotheses, discarding some of them altogether and modifying the probability of others. An advantage of the model is that evidence can be used whenever it is available, not being forced to obtain sensor data every step, a difference to many standard filter models.

The EWE concept was implemented specifically for agents participating in the RoboCup simulation league tournaments. Since it is slower than the conventional approaches, efficiency considerations had to be made. For this reason, EWE concept was limited to the estimation of only the most important world state variables, namely player position and ball movement. Originally, EWE was first used to determine ball position and velocity and later extended to also calculate the player position. For presentation purposes we will first describe calculation of the agent position, followed by the mechanism for ball localization. A first version of EWE was already implemented in the team LUCKY LÜBECK, but not yet activated for the Eurobocup Amsterdam 2000 tournament for lack of stability. The first use of EWE in an official tournament was in the Melbourne 2000 event[1].

2.1 Determining the Agent Position

Player position is a two-dimensional vector $p \in \mathbb{R}^2$. In the EWE concept, we use a two-dimensional polygon as corresponding multi-valued representation. It can be interpreted as a probability density distribution for the agent position that attains the value $1/A$ in the inside the polygon and 0 outside (with A the polygon area). Equally possible is the interpretation as the basis for a "polygon arithmetic" as generalization of standard interval arithmetic to the 2-dimensional plane. The probability view leads to slower algorithms, so we restricted ourselves to the polygon arithmetic view.

In EWE, one starts with an a priori model for the position. Data which is sent to the agent by the server, representing the noisy and inaccurate sensor readings, is called *raw data*. Each piece of raw data received represents an evidence which restricts the available possibilities for the true position. When a real-valued quantity s sent to the agent by the server, be it angle or distance, it is converted to a quantized value $\hat{s} = Q(s)$ via a *quantization function* $Q : \mathbb{R} \to \mathbb{R}$ which depends on the type of data (Corten et al. 1999). For the soccer server quantization functions 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 $\hat{s}$ cannot result from quantization). To determine its position, our agent uses its neck angle, its body orientation and flag landmarks. From the raw neck angle $\hat{\phi}_{\text{neck}}$ an interval $\Phi_{\text{neck}} = Q^{-1}(\hat{\phi}_{\text{neck}})$ of possible (true) neck angles is computed. The orientation of the view cone (which is the sum of body orientation and neck angle) is obtained from the observed angle of the field border lines, again yielding an interval Φ_{view}. The interval

[1] We gratefully acknowledge the work of the MAINZ ROLLING BRAINS 1999 team on whose agent code the present work is based (Polani and Uthmann 1999).

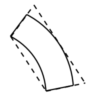

Fig. 1. Sector defined by an orientation and distance interval reconstructed by inverse quantization of raw server data representing the possible true relative positions of a landmark flag w.r.t. the agent. The solid line represents the form of the area as derived by the raw data. For the polygon algorithms, the area is slightly enlarged to the polygon denoted by the dashed lines.

arithmetic used now mimics the arithmetic procedure to determine agent orientation by single-valued variables. Thus, the angle interval for agent orientation is calculated to give $\Phi_{\text{orient}} = \Phi_{\text{view}} \oplus (-\Phi_{\text{neck}})$. $-$ denotes inversion of an interval at the origin, reversing its orientation (i.e. $-[a, b] = [-b, -a]$, where $a < b$). If the intervals were interpreted as probability distributions, $\oplus$ is the convolution operation, but we implemented $\oplus$ as interval arithmetic addition.

The landmark flag position data sent by the server give quantized values for distance and angle. Reconstruction via the inverse quantization gives an interval for possible true distances and another one for the possible true angles of the flag. With these, the set of possible flag positions relative to the agent 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 treatment by polygon arithmetic.

The same way the calculation of Φ_{orient} traces the computation of a single-valued variable for orientation, we trace the computation of the agent position from its orientation and the flag data obtained. We appropriately rotate P_{flag} (widening its area to take into account the interval structure of Φ_{view}) and, by shifting the result w.r.t. the absolute flag position, we calculate the polygon area P_{player} representing the possible player positions. This process is done for every flag seen in the current time step, each time yielding a set of agent positions consistent with the observed flag. The "true" position, i.e. the agent position in the soccer server must be consistent with all observations made and thus with the (set) intersection of all these sets. Also here a probabilistic formalism would have been a viable alternative. An estimate for the current position of the player is 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 typically 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, as averaging the position estimated directly from the raw data.

To estimate the player position, the CYBEROOS team independently implemented a mechanism similar to the one described in this section (private communication, Amsterdam 2000); so did the MAINZ ROLLING BRAINS (private communication, Melbourne 2000). They restricted themselves to the calculation of the agent position. This task can be seen as a special instantiation of the EWE concept. In fact, we used EWE first to estimate the ball state (Sec. 2.2) and only later applied it to the estimation of the player position.

2.2 Ball State Estimation

The generality of the EWE method allows us to determine ball movement in a conceptually similar fashion. For this, the approach of incorporating evidence needs to be applied to the *phase* instead of position space as in Sec. 2.1. The phase space is the set of the ball states which are fully represented by ball position *and* velocity. For simplicity, 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, the ball 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

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

where x is the location of the ball along the x-axis, v_x is its velocity and λ is the decay rate for the ball movement (Corten et al. 1999). The ball state is completely specified by the pair x, v_x because of our assumption that $y = 0$.

Denote the time before any evidence has been observed as t. At time t, the ball state is unknown. This means that 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 ball speed. The set of these possible initial ball states forms a rectangle in phase space (the full rectangle is not shown in Fig. 2 to not clutter the figure). When evidence about the ball is observed, one obtains a distance (and an angle which vanishes in our example). This distance defines a distance interval, restricting the possible x-positions of the ball to an interval. In phase space this defines the strip marked by the dotted lines in Fig. 2 (observation 1). After obtaining this evidence, the velocity, however, is still unknown. Due to the maximum velocity limits, the set of possible ball states in phase space is now delimited by the rectangle with solid lines in Fig. 2 (observation 1).

After one simulation step, by virtue of Eq. (1), for any given state in phase space we can predict the state in the next time step. In particular, the region of phase space that is consistent with observation 1 after a single simulation step is the oblique parallelogram depicted in Fig. 2. With a possible additional observation (no. 2 in Fig. 2), the requirement of consistency of the simulated phase space region with this observation restricts the region of possible ball states to the grey region in the figure. This obviously leads to a strong restriction of the set of possible velocities. During time this leads to a mutual restriction of x and v_x and thus to a quickly shrinking volume of phase space allowing a very precise localization of a ball as far away as 30–40 m after few time steps.

The method relies heavily on the mixing of the x and v_x-components of the feasible phase space region during time. By continued observations, the current

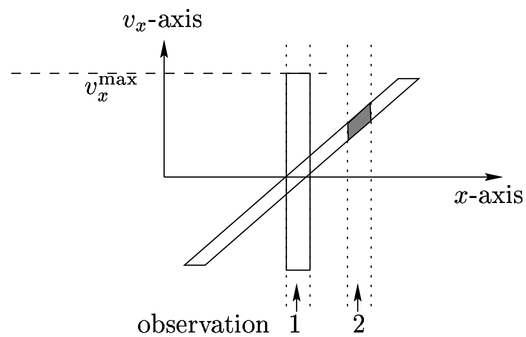

Fig. 2. Identifying position and velocity in phase space via observations

state of the system can be identified with increasing accuracy, similarly to the state identification models in chaotic systems, where under certain circumstances mixing effects also allow the accurate reconstruction of an initial system state.

3 A Simple Scenario

For illustration, we show some results from the method implemented in a regular player, with a full agent world model used in the Melbourne tournament. It therefore has more features than described above; we cannot discuss all particulars of the results presented here. We consider a player that repeatedly runs to the ball placed at the center, kicking it towards the goal.

Figure 3 shows the initial rectangle at the left. The horizontal width of the rectangle shows the initial uncertainty in determining the x-position of the ball. The agent now moves from its initial position at $x = -10$ m towards the ball. In subsequent simulation steps the rectangle is transformed into a parallelogram; new evidence defining vertical strips in the x/v_x-plane then increasingly restricts the set of possible ball states. Note that, since the ball is not moving in the initial phase of the simulation, the slices stay approximately at the same place. Thus the process of incrementally slicing parts from the possible positions is not spread out in x-direction as in the schematic Fig. 2. When the ball is kicked (the kick is modeled in the polygon simulation), the ball velocity jumps up and EWE is used to keep state model and observation synchronized.

Comparison of EWE with previously used ball position estimation algorithms shows that the ball position is indeed estimated to a much higher accuracy. Here, the agent regularly approaches the ball to kick it and therefore regularly obtains a more precise view of the ball. However, further experiments show that even for a ball as far as 30–40 m away from the agent, after a few simulation steps, the error in estimating the ball position quickly drops much below the size of the quantization levels.

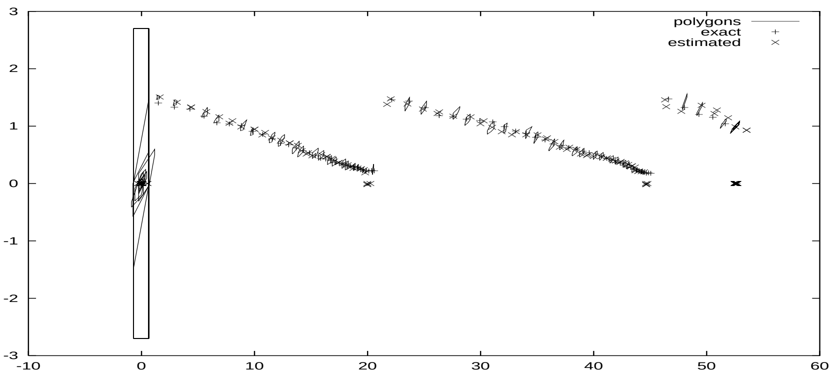

Fig. 3. The x/v_x-plane showing the development of the phase space estimation of the ball position x and velocity v_x.

4 Summary and Future Work

We introduced EWE, a general concept for the incorporation of new evidence into a internal world model and applied it to a scenario from the RoboCup simulation league, using it to estimate the player position and ball movement to a high degree of accuracy. Assuming an accurate model of world dynamics in a one-dimensional setting, the estimation of the ball movement even becomes near-optimal for the soccer server scenario. A number of difficulties with the current implementation, e.g. in presence of unmodeled noise or external influences will be discussed in future. We plan to extend our implementation to allow mixing of more than 2 dimensions and thus to better utilize existing evidence, also in more complex settings.

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