Modeling Observation Uncertainty for Soccer Playing Humanoid Robots

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***Abstract*— In recent years, humanoid robot soccer robots have shown increasingly robust and fast locomotion, making perception, world modeling and behavior control important. In this paper, we present the world modeling approach of the Darmstadt Dribblers humanoid robot team, which won the competitions in the RoboCup Humanoid KidSize League in 2009 and 2010. The paper focuses on modeling observation uncertainties originating from different contributing factors centrally in one module. This allows different state estimators to use this data in a consistent way, independently of the specific state estimation approach used.**

I. Introduction

Playing soccer is a challenging problem, especially for small autonomous systems like those in the RoboCup and FIRA robot soccer leagues, as robust bipedal locomotion is a necessary prerequisite for this task. Despite this difficulty, humanoid robots have shown increasingly reliable and agile bipedal locomotion abilities in recent years. This means perception, world modeling and behavior control are gaining importance, as the improved locomotion abilities can only be leveraged if the high level modeling and behavior system can make use of them.

The contribution of this paper is a detailed description of an approach for modeling observation uncertainties in resource constrained humanoid robot systems that explicitly identifies, considers and models different noise and error sources contributing to uncertainty in observations. It is shown how the improved modeling subsequently allows to achieve better results in state estimation modules based on parametric or sampling-based filters as well as a grid-based obstacle mapping approach.

II. Related Work

Probabilistic methods for state estimation are state of the art and are used by most successful teams in robot soccer. Both parametric approaches like Kalman Filters [1] and their variants like Multi-Hypothesis Kalman Filters [2] are used as well as sampling based approaches like particle filters [3] providing advantageous properties when multimodality and nonlinearities prohibit the use of parametric techniques. Rao-Blackwellized particle filters, representing a combination of parametric and sampling-based state estimation, are also used with success [4]. Recently, also constraint- and optimization-based methods [5] are used and are a promising direction for further research. This parallels research into the SLAM problem, where pose graph optimization methods [6],[7] are increasingly used for online applications in recent years.

In robot soccer, different state estimation tasks generally have different demands in terms of complexity, scope and difficulty. The two most prominent state estimation tasks that have to be fulfilled are estimation of the own pose of an autonomous soccer playing robot as well as estimation of the ball position. The self-localization task lends itself well to the implementation with a Monte Carlo Localization [8] approach using a particle filter due to its ability to represent ambiguous, multimodal state estimates as well as nonlinear motion and observation models. Ball Modeling on the other hand is often performed using a Kalman Filter or Multihypothesis Kalman Filter, as tracking of a single unambiguous object can be done well using these parametric filters [9],[10].

Both parametric and sampling-based filters rely on probabilistic motion and observation models in their prediction and update steps. Often [11],[12] the angular standard deviation of seen objects is a parameter that, while being configurable in many robot systems, stays fixed unless human intervention changes it. While using such a model works well if the parameters are well tuned, fixed noise estimates for sensors prevent leveraging the knowledge of the current robot state to achieve more accurate state estimation. For example, a goalie robot standing still inside the goal might generate much more accurate observations of the ball than his moving teammates. Not using this knowledge means that the robot generates state estimates with too high estimated uncertainty, effectively not using all the information available.

III. Hardware

Our autonomous humanoid soccer platform is based on the HR30 platform by the Hajime research institute. With additions and modifications the current model is denoted DD2010 (Fig. 1). It has 21DOF, all of which are actuated by Robotis Dynamixel servo motors (18xRX-28, 3xRX-64). Low level and hard real-time control are provided by a microcontroller board with a Renesas SH2 CPU [13], while high level cognition runs on a FitPC2 board in the back of the robot, featuring an Atom Z530 CPU. Both systems are connected by a serial (RS232) connection. Among the internal sensors of the robot are a 3 axis accelerometer board

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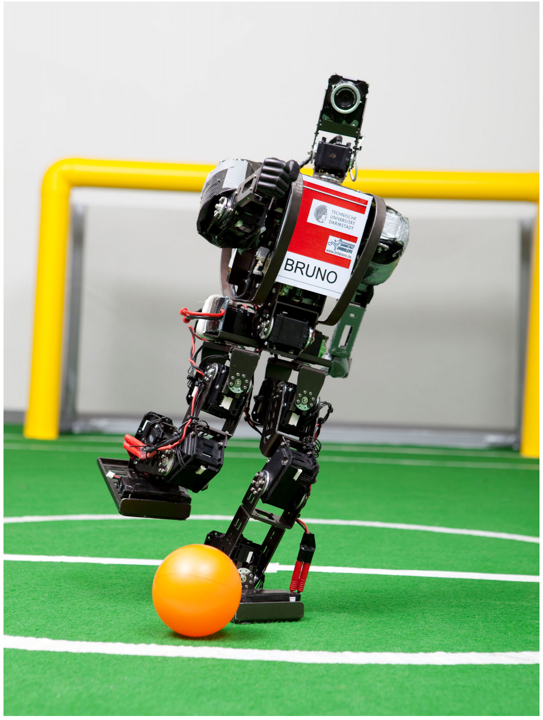

Fig. 1: DD2010 humanoid robot (©Katrin Binner)

as well as 3 single-axis angular rate gyros. The joint servos can be queried to report their measured joint angles. A more comprehensive overview is available in [14].

IV. Modeling Uncertainty

For many applications in robotics, uncertainty in perception can be minimized by carefully selecting sensors and having very narrowly defined conditions and states the robot system might experience. Such approaches are leveraged in industrial robotics, but for the size- and weight-constrained systems in autonomous robot soccer such an approach is rarely feasible. For this reason, uncertainties have to be considered explicitly.

A. Modeling Motion Uncertainty

On the platform under consideration, odometry data can be estimated from the known desired footsteps that are generated on the microcontroller. This odometry information is impeded by significant uncertainties, as actual displacement and slippage cannot be measured directly. Experiments and experience in competitions showed that slippage during turning of the robot was a major source of error and exhibited very irregular and nonlinear characteristics. For this reason, gyroscope data is used for the rotational part of odometry.

Using this system, noise parameters for translational and rotational parts of odometry can be determined by experimentation. When optimizing parameters using a ground truth recording system, care has to be taken not to overfit parameters, as certain situations in robot soccer matches like collisions of robots and wear in actuators might lead to higher odometry errors than commonly observed under ideal conditions. For this reason, odometry error generally is modeled to be larger than commonly observed, in order to be robust against mentioned situations.

B. Modeling Observation Uncertainty

Small scale humanoid robots exhibit varying and potentially large uncertainties in vision-based observations for a multitude of reasons. First of all, camera systems might not provide exact timestamps of the images they generate. This is the case for our humanoid robots, as a commercial webcam (Philips SPC-1300) is used here. While industrial cameras generally support exact time stamping, they often only provide Bayer pattern data, which has to be preprocessed on the host CPU to retrieve a color image. To relieve the CPU of this task, we use a commercial webcam which provides YUV422 images through processing on a built in ASIC and streams these images via USB 2.0 with a resolution of 640x480 pixels at 30Hz. In comparison to the industrial cameras we tested, we also found the SPC-1300 webcam to have favorable sensitivity and robustness to low and varying lighting conditions. The camera uses a rolling shutter, meaning that images display warping if they are taken during motion of the camera. While methods for compensating for this warping using knowledge about the camera's movement exist [15], in our approach the effect can be subsumed in the additional angular variance of observations when the camera is moving fast.

The intrinsic parameters of the camera are calibrated using a publicly available toolbox [16] and are used by the image processing pipeline. Our humanoid robots use measured joint angles of the kinematic chain from estimated foot on ground to the camera for estimating the extrinsic camera parameters with regards to the robot coordinate system. Using the intrinsic and extrinsic parameters, vectors of detected objects can be intersected with the ground plane for an estimate of their distance to the robot. For objects of known size like the ball, size-based distance estimation is also feasible and used. As the low weight camera sensor is mounted on a pan-tilt unit, the fast actuation of the pan and tilt servos is a major source of error, due to causing motion blur in camera images, as well as angular estimation errors due to errors in timestamp synchronization between read out servo joint values and image timestamps. This error is dependent on the angular rates of the pan and tilt servos of the robots camera head:

$$\omega_{\text{head}}(t) = \begin{pmatrix} \omega_{\text{tilt}}(t) \\ \omega_{\text{pan}}(t) \end{pmatrix} \tag{1}$$

Another major source of observation uncertainty is movement of the platform: As soon as the robot is moving, shaking of the platform leads to higher observation uncertainty. Due to the low available computational power and weight restrictions, approaches for image stabilization [17] are not feasible in our scenario, thus modeling this shaking motion as additional noise is the approach used in our system. The amount of noise due to movement of the robot is dependent on the movement state of the robot, e.g. the translational and angular velocities

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of the robot on the playing field:

$$\dot{\mathbf{x}}_{\text{robot}}(t) = \begin{pmatrix} \dot{x}_{\text{robot}}(t) \\ \dot{y}_{\text{robot}}(t) \\ \dot{\theta}_{\text{robot}}(t) \end{pmatrix} \tag{2}$$

Thus by considering the main contributing factors to errors in camera perception, we propose the following adaptive approach for modeling camera observation standard deviations using observation angle α around the pitch axis as well as observation angle β around the yaw axis:

$$\sigma_\alpha(t) = \sigma_\alpha^{\text{base}} + \sigma_\alpha^{\text{head}}(\omega_{\text{head}}(t)) + \sigma_\alpha^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t)) \tag{3}$$

$$\sigma_\beta(t) = \sigma_\beta^{\text{base}} + \sigma_\beta^{\text{head}}(\omega_{\text{head}}(t)) + \sigma_\beta^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t)) \tag{4}$$

Here, $\sigma_{\alpha_{base}}$ and $\sigma_{\beta_{base}}$ are the base angular standard deviations that are always affecting perceptions performed through the image processing system of the robot. Errors/noise due to imperfect calibration and limited accuracy of the vision system are subsumed here. On our system, we found that the noise the object detections by the image processing system in image coordinates is low compared to noise introduced by the effects due to motion of the camera.

$\sigma_\alpha^{\text{head}}(\omega_{\text{head}}(t))$ and $\sigma_\beta^{\text{head}}(\omega_{\text{head}}(t))$ represent added noise due to head camera motion. In our system, this added noise is modeled by simple linear functions:

$$\sigma^{\text{head}}(\omega_{\text{head}}(t)) = \begin{pmatrix} c_{\text{tilt}}\omega_{\text{tilt}}(t) \\ c_{\text{pan}}\omega_{\text{pan}}(t) \end{pmatrix} \tag{5}$$

with c_{tilt} and c_{pan} being constant factors determined through experimentation. Our system always waits for updated joint values after receiving an image, so proper extrinsic camera parameters can be determined. From the difference between joint values from preceding to current image, approximate angular rates of the head servos $\omega_{\text{head}}(t)$ can be determined.

$\sigma_\alpha^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t))$ and $\sigma_\alpha^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t))$ represent added noise due to locomotion of the whole robot. Experiments have shown that any movement of the legs leads to increased error in observation angles, with no distinct correlation between different movement patterns and different noise characteristics in observation that could be leveraged. For this reason, the same added standard deviation due to movement of the robot is used regardless of the exact movement pattern:

$$\sigma^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t)) = \begin{cases} 0 & \text{if } \dot{\mathbf{x}}_{\text{robot}}(t) \text{ is } (0,0,0)^T, \\ \sigma^{\text{moving}} & \text{otherwise.} \end{cases} \tag{6}$$

While this approach works well for our humanoid robots, other systems might exhibit strong correlations between different movement schemes and resulting noise in observations which could be leveraged by the use of more sophisticated functions for the approximation of $\sigma^{\text{loc}}(\dot{\mathbf{x}}_{\text{robot}}(t))$.

V. Ball Modeling

State estimation of the ball is performed by employing a Kalman Filter. The ball state estimate incorporates the position as well as velocity of the ball in cartesian robot coordinates:

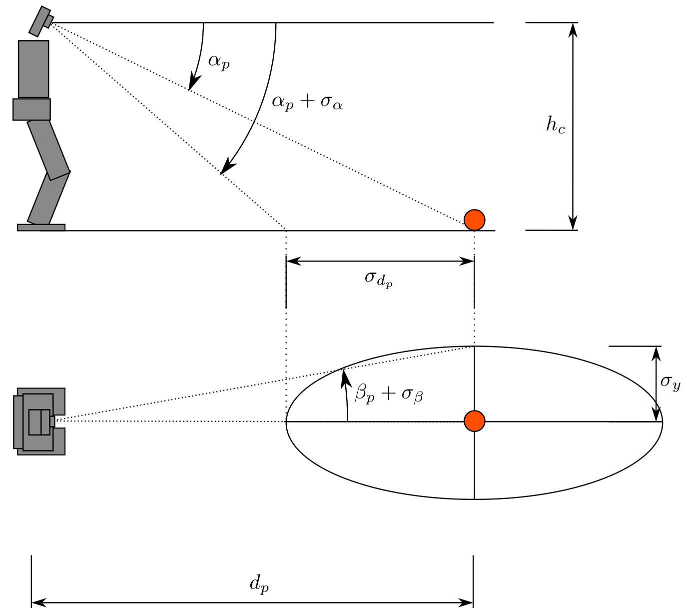

Fig. 2: Approximation of measurement covariance in state space from observation angular standard deviations σ_α and σ_β

$$\vec{\mathbf{x}}(t) = \begin{pmatrix} p_x(t) \\ p_y(t) \\ v_x(t) \\ v_y(t) \end{pmatrix} \tag{7}$$

Ball state estimation is performed using robot coordinates, so it is not affected by errors in the robot's own pose estimate. To account for robot motion, the ball state is transformed by odometry data, which is sufficiently accurate for the timeframes that are important in the highly dynamic robot soccer scenario. The observation update can be performed by considering two different sources of information: The robot's own camera as well as ball state estimates received from other robots by wireless communication.

A. Ball Model Update from Camera Data

Using the robot's own camera, the ball state is only partially observable, as only the position and size in the image can be detected, while the velocity remains unknown. In the case of the ball, two approaches for estimating the distance are feasible: Intersecting the ball perception vector with the ground plane as well as size-based measurements. The projection-based method is shown in Fig. 2. Here, the ball perception vector is projected onto the ground along with the angular standard deviation σ_α around the pitch axis and σ_β around the yaw axis to construct an approximate observation covariance matrix in state space. The standard deviation of the projection-based distance estimate is:

$$\sigma_{d_p} = \frac{h_c}{\tan(\alpha_p + \sigma_\alpha)} - \frac{h_c}{\tan(\alpha_p)} \tag{8}$$

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This distance estimate and the accompanying standard deviation alone can be used for the observation update. However, as our image processing system can also provide a size-based distance estimate, we also leverage this information when it is available. It can be more accurate than the projection-based distance estimate, especially if the ball is far away and the robot is moving. Both measurement methods have very different error characteristics, so we consider them to be independent given the ball state and fuse both size- and projection-based estimates using optimal fusion of two Gaussian estimates. The projection-based distance estimate (d_p, σ_{d_p}) and the size-based estimate $(d_s, \sigma d_s)$ are fused to get a fused estimate (d_f, σ_{d_f}). The optimal gain is:

$$k_f = \frac{{\sigma_{d_p}}^2}{{\sigma_{d_p}}^2 + {\sigma_{d_s}}^2} \tag{9}$$

resulting in the fused distance mean

$$d_f = d_p + k_f(d_s - d_p) \tag{10}$$

and the fused distance variance

$${\sigma_{d_f}}^2 = (1 - k_f){\sigma_{d_p}}^2 \tag{11}$$

Using this approach, the error models for both size- and projection-based distance estimation can be adjusted and learned independently. It remains to be shown how the directional standard deviation σ_β in observation space is projected into state space to arrive at a standard deviation σ_y in state space that models the directional uncertainty around the vertical axis. For this, again referring to Fig. 2 we use:

$$\sigma_y = \tan(\sigma_\beta) d_f \tag{12}$$

Knowing σ_y and σ_{d_f}, an approximate covariance matrix R_{base} for the Kalman Filter observation update is:

$$R_{\text{base}} = \begin{pmatrix} {\sigma_{d_f}}^2 & 0 \\ 0 & {\sigma_y}^2 \end{pmatrix} \tag{13}$$

For readability, the example in Fig. 2 shows a scenario where the directional angle to the ball percept β_p is 0 (i.e. the ball is directly in front of the robot). For arbitrary angles β_p, R_{base} has to be transformed by the following rotation matrix:

$$M(\beta_p) = \begin{pmatrix} \cos(\beta_p) & -\sin(\beta_p) \\ \sin(\beta_p) & \cos(\beta_p) \end{pmatrix} \tag{14}$$

The transformed covariance matrix used for the Kalman update is then given by:

$$R_{\text{rotated}} = M(\beta_p) R_{\text{base}} M(\beta_p)^T \tag{15}$$

The observation mean has also be transformed to reflect the described transformations. This transformation is straightforward and omitted here for brevity.

B. Ball Model Update from Team Data

In the RoboCup soccer scenario, robots may communicate among each other and exchange their ball state estimates. This is used extensively our team. Unlike the observation from camera frames, communicated ball estimates from team members provide a full state estimate including ball velocity.

If a robot did not detect the ball with its own camera, it will update the ball state estimate from the best (i.e. lowest uncertainty) team estimate available after the uncertainty of the own estimate has surpassed a threshold value. As mentioned earlier, ball state estimation is performed in robot coordinates. For this reason, estimates have to be transformed into world coordinates to be useful for other robots. This is performed by multiplying both the top left and lower right 2x2 matrices of the state covariance with a rotation matrix representing the robot orientation as well as transforming the mean vector into world coordinates.

To account for various sources of error (uncertainty in own and other robot's pose estimate, imperfect synchronization of timestamps) the teammate's covariance is multiplied by a factor to subsume the various sources of added uncertainty. This covariance is then used for the Kalman update of the ball state estimate. In practice, the fast exchange of ball state estimates by all three robots on the field implies that the ball position and velocity are known to the team at nearly all times, as the reader might verify by looking at videos of the RoboCup 2010 final game showing internal world model data [18].

VI. Self Localization

We use a Monte Carlo Localization [8] approach for pose estimation of our soccer playing autonomous robots. The approach as described in [19] is made more robust by employing sensor resetting with a preceding filtering step which we call Particle Maturing MCL. Here, new particle candidate (template) poses are generated from single incoming observations of landmarks, for example perceptions of goal poles or field line crossings. These template poses do not get inserted into the particle set right away but have to mature by getting updated from consistent observations of different features over time before they become candidates for insertion into the particle set by sensor resetting. This greatly enhances robustness of the system, as particle templates generated from erroneous perceptions will get purged in the maturing step, before they are inserted in the particle set used for pose estimation.

For determining the particle weights in the observation update step of the filter, we utilize the observation standard deviations described earlier. For each particle m, the angular differences between the current measurement and the state estimate provided by the particle ${x_t}^{[m]}$ along the pitch and vertical axes are used for determining the particle weight:

$$\delta_\alpha^{[m]} = |\alpha_p - \alpha_{{x_t}^{[m]}}| \tag{16}$$

$$\delta_\beta^{[m]} = |\beta_p - \beta_{{x_t}^{[m]}}| \tag{17}$$

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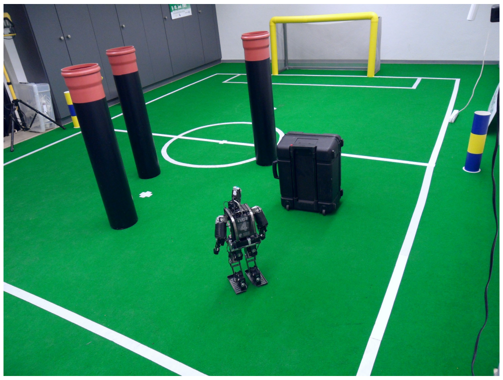
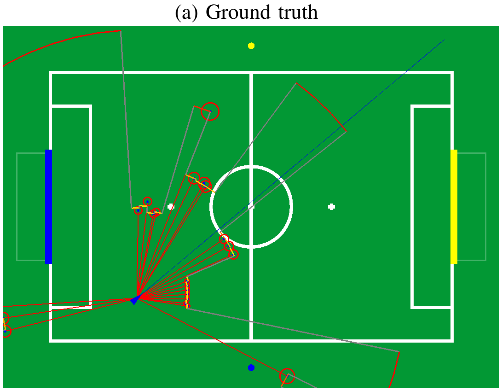
These are then used for computing the particle weight:

$$w_t^{[m]} = \mathcal{N}(\delta_\alpha^{[m]}, \sigma_\alpha(t)^2)\mathcal{N}(\delta_\beta^{[m]}, \sigma_\beta(t)^2) \tag{18}$$

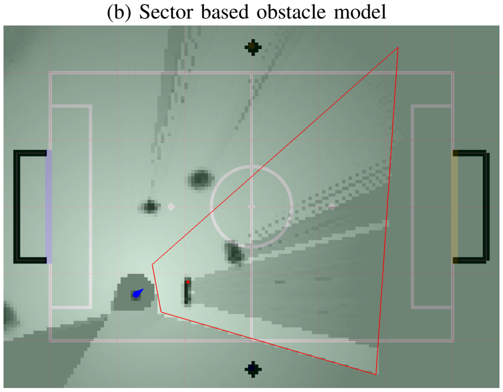
Here, $\sigma_\alpha(t)$ and $\sigma_\beta(t)$ are the observation standard deviations as defined in Equations (3) and (4).



(a) Ground truth



(b) Sector based obstacle model



(c) Grid based obstacle model

Fig. 3: Comparison of obstacle modeling approaches: (a) shows a real world scene featuring multiple obstacles. (b) shows the robot-centric obstacle model used by the Darmstadt Dribblers in the last 3 years, while (c) shows the grid-based obstacle model currently in development.

VII. Obstacle Modeling

In the 2009 and 2010 RoboCup competitions, our robots utilized a sector-based, robot centric obstacle model. Using this model, the obstacle distance in 72 sectors around the robot is tracked without explicit consideration of measurement uncertainty. While being sufficient for local obstacle avoidance, updating the model by odometry is only possible for short distances moved by the robot due to coarse discretization of the state space in conjunction with the used polar coordinate system.

As the model does not use a probabilistic representation of occupancy, there is no model of free space and no information about non-occupied areas: It remains unknown if the sectors marked as unoccupied contain free space, or if they just have not been observed for a longer time (and are occupied).

As can be seen in Fig. 3b), the width of some obstacles is overestimated due to noisy or erroneous direction estimates of the panning camera. In contrast to this, a grid-based method currently in development utilizes an occupancy grid map representation [20] of the environment commonly used in SLAM. Our image-based obstacle detection system is capable of detecting free space and obstacles inside the field of view of the camera, which makes it possible to use similar sensor models like those used for mapping with ultrasonic sensors. The obstacle perceptions taken with the onboard camera are again subject to angular noise $\sigma_\alpha(t)$ and $\sigma_\beta(t)$ as given in Equations (3) and (4). These noise characteristics are used by the sensor model for updating the obstacle map.

Fig. 3c) shows an dynamic occupancy grid map learned in a real world situation. It is worth noting that the robot not only has a detailed map of occupied (black) areas, but a just as detailed map of free as well as unknown areas.

Thus, using the occupancy grid mapping approach, an occupancy estimate of every location on the playing field is available. These estimates can in turn be used for path planning, behavior control and gaze control of soccer playing humanoid robots, which are directions of ongoing work.

VIII. Results

The proposed approach was tested with ground truth data as well as during the RoboCup competition in Singapore.

A. Quantitative Evaluation

For evaluation of the proposed system, an approach for evaluating the overall system performance of both self localization and ball modeling at the same time is used. For measuring state estimation quality when the ball is stationary we place the ball in the middle of the center circle. The ground truth of the ball position is thus precisely known. Our metric for the quality of state estimation is the RMSE of the ball position estimate in world coordinates given ground truth. This metric relies on both self localization as well as ball modeling and therefore is well suited to determine overall system performance. The robot walks a predefined trajectory while all relevant sensor data are recorded. This dataset can then be used to vary parameters like the observation uncertainties σ_α and σ_β and produce repeatable results.

For determining state estimation quality when the ball is moving, the ball was kicked towards a goalie robot and the data was recorded as explained before.

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As can be seen in the results in Table I, the approach using adaptive observation uncertainties copes well with both situations, while fixed values produce inferior results in one of the scenarios.

Observation model	RMSE static ball	RMSE moving ball
Fixed σ_α, σ_β = 5°	25.3 cm	9.4 cm
Fixed σ_α, σ_β = 15°	15.7 cm	16.6 cm
Adaptive σ_α, σ_β	15.8 cm	10.3 cm

TABLE I: RMSE of ball state estimate from ground truth using different observation model settings. The first two observation models use fixed noise estimates, while the third one uses the proposed adaptive approach.

B. Qualitative Evaluation

During the RoboCup 2010 competition, the proposed approach was used on all autonomous humanoid soccer robots used by the Darmstadt Dribblers team for the soccer matches in the Humanoid KidSize League. Over the course of the competition, our robots managed to score 74 goals. The majority of shots towards the Darmstadt Dribbler's goal were repelled by the goalkeeper robot, with only 2 goals scored against the Dribblers.

As onboard data was recorded during all matches for subsequent debugging and evaluation purposes, a thorough evaluation of world modeling and state estimation of our robots in competitive conditions is possible. This proved very useful as many faults cannot be detected, much less explained, without having ground truth data (video) synchronized with recorded internal robot data. Ground truth for the data recorded at RoboCup 2010 was not annotated so far, so a statistical evaluation cannot be presented.

Video footage of the final match in the Humanoid KidSize League synchronized with internal robot data is publicly available online [18].

IX. Conclusions

In this paper, we presented the world modeling approach used in the Darmstadt Dribbler's autonomous soccer playing robots with a focus on modeling observation uncertainties caused by different contributing factors. The proposed approach reduces the amount of parameters that need to be estimated in robot systems, as the observation standard deviations are estimated in a principled way in a single module and can subsequently used by all other state estimation modules. As examples for such modules we have shown how the proposed approach can be leveraged in parametric filters like a Kalman Filter used for ball state estimation, non-parametric filters like the particle filter approach we use for robot pose estimation, as well as in sensor models for grid-based mapping.

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