Integrating Simple Unreliable Perceptions for Accurate Robot Modeling in the Four-Legged League*

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Abstract. The perception and modeling of other robots has been a topic of minor regard in the Four-Legged League, because of the limited processing und sensing capabilities of the AIBO platform. Even the current world champion, the GermanTeam, abandoned the usage of a robot recognition. Nevertheless, accurate position estimates of other players will be needed in the future to accomplish tasks such as passing or applying adaptive tactics. This paper describes an approach for localizing other players in a robot's local environment by integrating different unreliable perceptions of robots and obstacles, which may be computed in a reasonable way. The approach is based on Gaussian distributions describing the models of the robots as well as the perceptions. The integration of information is realized by using Kalman filtering.

1 Introduction

The Four-Legged Robot League is one of the official leagues in RoboCup, in which a standardized robot platform is used, namely the Sony AIBO, which has quite limited perceptual capabilities. The main sensor of the Sony AIBO is a camera located in its head. The head can be turned around three axes, and the camera has a field of view of approximately 57° by 42°. As the main sensor of the robot is a camera, all objects on the RoboCup field are color coded. For robots, this leads to two different tricot colors, i. e. red and blue, which are applied to the robots as patches (Fig. 1).

During actual RoboCup games, robots are hard to perceive. Especially the blue tricots are often indistinguishable from black or dark grey. The relatively large distances on the field as well as the limited field of view—compared to robots in other leagues that are allowed using omni-directional sensors—make it

* The Deutsche Forschungsgemeinschaft supports this work through the priority program "Cooperating teams of mobile robots in dynamic environments".

G. Lakemeyer et al. (Eds.): RoboCup 2006, LNAI 4434, pp. 474–482, 2007.

a) b)

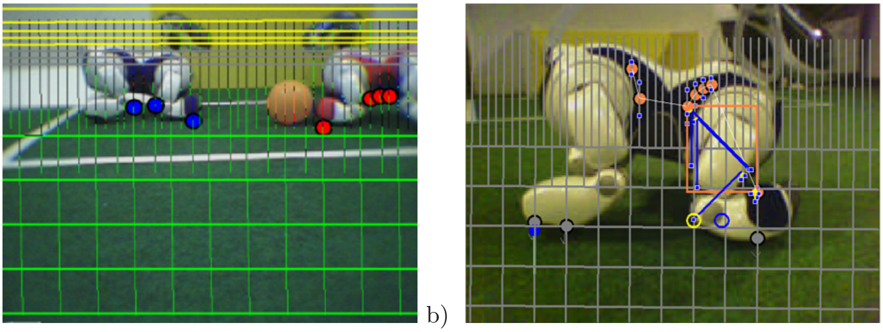

Fig. 1. Detection of robots by using a grid of scan lines

almost impossible for a single robot to compute accurate estimates of all players on a field based on its own perceptions.

Despite of the existence of robot detection algorithms [1,2,3,4], often only simple obstacle information [5,6] is used for navigation. Nevertheless, a localization for robots is needed, if techniques such as passing towards teammates or tactics which are adapting to the opponent's positions should be applied. Because of the limited field of view, and the unreliability of the available robot perceptions, sophisticated techniques for modeling are needed.

The approach presented in this paper aims at computing accurate estimates of player positions in the robot's local environment by using probabilistic modeling techniques. It does not incorporate communication with other robots and depends therefore on visual perceptions. To improve estimates, information different from explicit robot perceptions is additionally integrated, i. e. occupied spaces as well as free spaces on the field.

In the Four-Legged League domain, player position estimation has been a topic of minor regard, so far. Nevertheless, several similar works about modeling position and velocity of the ball using Kalman filters [3] or Rao-blackwellized particle filters [7] have been published. Also the integration of different perceptions for improving estimates of the ball position has been described by [2].

This paper is organized as follows: Section 2 presents the perceptions which are used for computing estimates. The estimation approach is described in Sect. 3. Experimental results are presented in Sect. 4. The paper ends with a conclusion and an outlook on future work in Sect. 5.

2 Perceptions

The work described in this paper is based on the software of the GermanTeam 2005 [4] and therefore uses its vision system. This system processes images of a resolution of 208 × 160 pixels, but actually considers only a horizon-aligned grid of less pixels [8] (see Fig. 1). Each grid line is scanned pixel by pixel. During the scan, each pixel is classified by color. A characteristic series of colors or a pattern of colors is an indication of an object of interest.

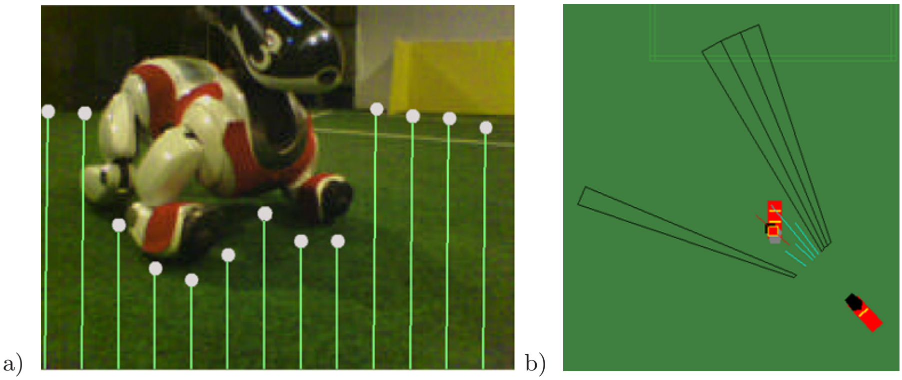

Fig. 2. Detection of obstacles. a) Lines scanning for unoccupied space. The bright dots indicate the end of the free field. b) A similar situation represented in the robot's world model. The short lines indicate the free space among the robot and another robot. The sectors surrounded by black lines are regions which are considered to be unoccupied.

Robot Detection. To find the indications for other robots, the scan lines are searched for the colors of the tricots of the robots. The scan lines are followed until the green of the field appears (cf. Fig. 1a). Thus the foot points of the robot are detected. From these foot points, the distance to the robot can be determined. A refinement for determining the position of the robot is the extraction of the position of a front foot from the image [4] (cf. Fig. 1b). Using this simple approach, a recognition of a robot's rotation is not possible. The only information is the relative position of a robot. The small tricot elements cause a detection of robots at a distance of more than 1.5m to be highly unlikely. The precision of these percepts is shown in Sect. 4, their integration into a robot position estimation is described in Sect. 3.2.

Obstacles and Free Space. A concept different from the recognition of robots is the detection of obstacles [6,5]. Instead of searching robot features in an image, the unoccupied regions, i. e. the green field including the white lines, are determined (cf. Fig. 2a). Thus, areas not classified as free space have to be considered to be obstacles. Though obstacles don't necessarily need to be robots (e. g. beacons, goals, and the feet of a referee would also be classified as obstacles), they can be used for improving the estimation of a robot position (cf. Sect. 3.2). In contrast to this positive information, this perception additionally bears negative information about regions in which no robots are located. The usage of this perception is described in Sect. 3.3.

Collisions. A completely proprioceptive kind of percept is information about the current physical state of the robot, i. e. the correctness of the calculated camera position or the odometry. Both information may be disturbed by collisions with other robots and hence lead to disturbed perceptions. For instance in [9], it has been shown that it is possible to compute reliable information about collisions occurring to a moving AIBO robot. The use of this information is described in Sect. 3.1.

3 Robot Models

Since the number of players that could be observed from a robot's position varies, a set[1] of actual estimations—in the following termed as *hypotheses*—has to be kept and updated. A robot hypothesis H is modeled as a Gaussian distribution. Therefore it is a tuple consisting of a mean μ_h which describes the position of the robot and a covariance Σ_h which models the uncertainty of the position. Since the image processing algorithms used for this work are not capable of recognizing a robot's relative rotation, two-dimensional distributions are used. All hypotheses are kept relative to the observing robot in polar coordinates which consist of a distance d and an angle α.

$$\mu_h = \begin{pmatrix} d \\ \alpha \end{pmatrix}, \quad \Sigma_h = \begin{pmatrix} \mathrm{var}(d) & \mathrm{cov}(\alpha, d) \\ \mathrm{cov}(d, \alpha) & \mathrm{var}(\alpha) \end{pmatrix} \tag{1}$$

New hypotheses may be created from perceptions of robots (cf. Sect. 3.2) whilst existing hypotheses are maintained by a Kalman Filter [10,11] which incorporates the robot's motion (cf. Sect. 3.1) and integrates different perceptions (cf. Sect. 3.2–3.3) to improve the estimation of player's positions. Every hypothesis is considered to be a single robot that is tracked. Nevertheless, it is possible that noisy perceptions lead to different hypotheses describing the same robot. These effects are addressed by the mechanisms described in Sect. 3.4. The general approach—the structure of which is similar to [12]—is depicted in Fig. 3.

3.1 Motion Update

On every execution of the modeling module, all existing hypotheses have to be updated according to the motion $(\Delta x, \Delta y, \Delta\alpha)$ of the observing robot since the last execution. This information is gained from the robot's odometry. The update also includes noise depending on the quantity of the motion. The mean of the hypothesis is updated by

$$\alpha^+ = \mathrm{atan2}(\sin(\alpha^-)d^- - \Delta y, \cos(\alpha^-)d^- - \Delta x) - \Delta\alpha \tag{2}$$

$$d^+ = \sqrt{(\sin(\alpha^-)d^- - \Delta y)^2 + (\cos(\alpha^-)d^- - \Delta x)^2}. \tag{3}$$

The uncertainty caused by the robot's motion is added to the hypothesis' covariance matrix Σ by

$$\Sigma^+ = J_1 \Sigma^- {J_1}^T + J_2(1 + e_c)\Sigma_\Delta {J_2}^T + \Sigma_N \tag{4}$$

where two Jacobian matrices J_1 and J_2 are defined as

$$J_1 = \frac{\partial \begin{pmatrix} \alpha^+ \\ d^+ \end{pmatrix}}{\partial \begin{pmatrix} \alpha^- \\ d^- \end{pmatrix}}, \quad J_2 = \frac{\partial \begin{pmatrix} \alpha^+ \\ d^+ \end{pmatrix}}{\partial \begin{pmatrix} \Delta x \\ \Delta y \\ \Delta\alpha \end{pmatrix}}. \tag{5}$$

[1] Actually, the implementation keeps red and blue robots in two different sets, but this detail is not addressed in this general description of the approach.

```
ROBOTMODELING (Hypotheses, RobotPerceptions, Obstacles, Odometry)
    for each Hypothesis H:
        MOTIONUPDATE (H, Odometry)
    for each RobotPerception P:
        if INTEGRATIONPOSSIBLE(Hypotheses, P)
            INTEGRATE(P, BESTMATCH(Hypotheses, P))
        else
            Hypotheses add P
    for each Hypothesis H:
        UPDATEBYPOSITIVEOBSTACLES (H, Obstacles)
        UPDATEBYNEGATIVEOBSTACLES (H, Obstacles)
        if LOWQUALITY(H)
            Hypotheses remove H
        else if (H*| MERGINGPOSSIBLE(H*, H)) exists
            MERGE(H, H*)
    end
```

Fig. 3. The general operation of the robot modeling

The matrix Σ_Δ contains information about the uncertainty of the robot's motion and is provided by the odometry model. Additionally, collisions may be taken into account by multiplying the matrix with a factor e_c. This factor is zero, if no collisions occur. In case of a collision, a positive value reflects the higher uncertainty of odometry. Through the matrix Σ_N, constant white noise is added reflecting the uncertain motion of the observed robots. This causes the variance to grow constantly in absence of any measurements. Adequate values for Σ_Δ, Σ_N and e_c have to be determined empirically.

3.2 Robot Percepts and Positive Obstacle Information

Before adding new hypotheses to the list, all measurements are tried to be integrated with existing estimations. In a first step, a percept is converted to a hypothesis H_m. Its mean μ_m is the position of the measurement. A corresponding covariance matrix Σ_m has to be precomputed from a set of measurements (as those made for Fig. 4a). This can be refined by providing matrices for different distances and angles and using interpolations of these for new measurements.

The new hypothesis has now to be associated to an already existing robot hypothesis H_r. The Mahalanobis distance

$$d_M(H_r, H_m) = (\mu_r - \mu_m)^T(\Sigma_r + \Sigma_m)^{-1}(\mu_r - \mu_m) \tag{6}$$

provides a distance measure that describes the compatibility of two hypotheses, indicating whether both could refer to the same robot. After the closest hypothesis H_r has been found and $d_M(H_r, H_m)$ is below a maximum acceptable

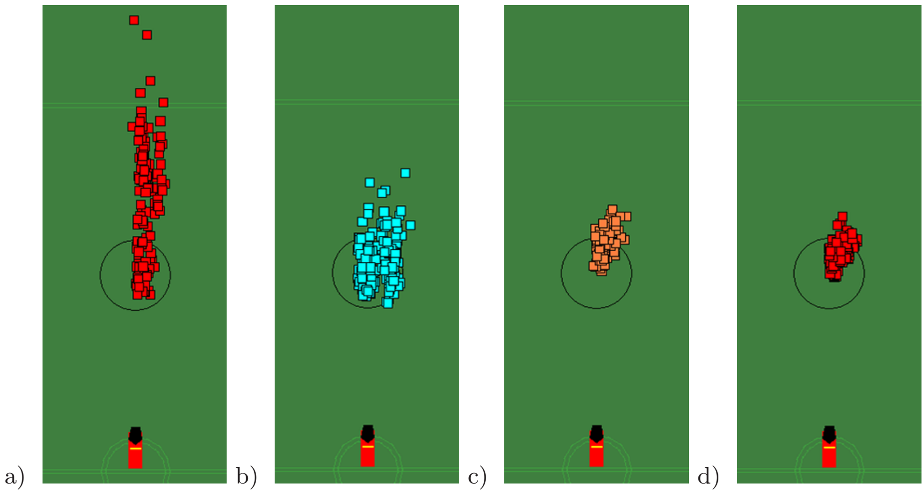

Fig. 4. A robot standing at a distance of 80cm is perceived and its position is estimated. Every dot indicates an estimate, the black circle surrounds the ground truth position. a) The plain perception from the vision system. b) Plain obstacle positions as used by 3.2. c) The modeled position using robot perceptions only. d) The modeled position using robot and obstacle perceptions.

distance, H_m is integrated:

$$\mu_h^+ = \mu_h^- + \Sigma_h^-(\Sigma_h^- + \Sigma_m)^{-1}(\mu_m - \mu_h^-) \tag{7}$$
$$\Sigma_h^+ = \Sigma_h^- - \Sigma_h^-(\Sigma_h^- + \Sigma_m)^{-1}\Sigma_h^- \tag{8}$$

Otherwise, the measurement will be added to the list as a new hypothesis.

In general, perceived obstacles are treated similar to robot percepts, solely the usage of a lower threshold κ_o for hypothesis association is needed and the possibility of adding new hypotheses to the list does not exist. The mean μ_o is computed from a set of adjacent obstacle segments (cf. Fig. 2a). Of course, the values for the covariance matrix Σ_o have also to be determined empirically, since they differ strongly from the robot percept values (cf. Fig. 4b).

3.3 Negative Obstacle Information

In opposite to the previous two perceptions, which denote the presence of robots, the negative obstacle information, i. e. empty regions of the field, denotes absence of any robots. This information is quite useful for the elimination of false positives as well as for a quick update of the world model in case of a robot kidnapping (which have e. g. been picked up by a referee). The incorporation of this information is done via checking the inclusion of every hypothesis' mean μ_h inside every sector recognized as being empty (cf. Fig. 2). In case of such an inclusion, white noise is added to the corresponding covariance matrix.

3.4 Maintenance of Hypotheses

While maintaining a list of hypotheses, it has not only to be taken care of removing elements, e. g. those with an uncertainty above a given threshold. The possibility of having two hypotheses describing the same robot must also be considered. This effect is detected by using a heuristic derived from the limits of the used image processing approaches: Two hypotheses H_1 and H_2 whose means μ_1 and μ_2 are located very close to each other can not be distinguished anymore by robot percepts in a reasonable way. These two hypotheses become merged, i. e. they are viewed as a sum-of-two-Gaussians distribution and replaced by a single Gaussian with the same mean and covariance. This is accomplished by

$$\mu_n = w_1\mu_1 + w_2\mu_2 \tag{9}$$
$$\Sigma_n = w_1\Sigma_1 + w_2\Sigma_2 + w_1 w_2(\mu_1 - \mu_2)(\mu_1 - \mu_2)^T \tag{10}$$

where the relative weight of the two hypotheses is controlled by

$$w_1 = \frac{P_{H_1}(\mu_{H_1})}{P_{H_1}(\mu_{H_1}) + P_{H_2}(\mu_{H_2})}, \quad w_2 = \frac{P_{H_2}(\mu_{H_1})}{P_{H_1}(\mu_{H_1}) + P_{H_2}(\mu_{H_2})} . \tag{11}$$

4 Experimental Results

The approach described in this paper has been implemented using the framework of the GermanTeam. Several experiments using an AIBO on an original Four-Legged League field have been conducted. To demonstrate the improvement of player position estimates by using the proposed modeling techniques, the quality of hypotheses while sensing different robots at different distances has been measured. One example is depicted in Fig. 4.

To demonstrate the capability to model several robots simultaneously as well as assigning measurements to different robots of the same color, different settings including a number of robots have been investigated (cf. Fig. 5). These

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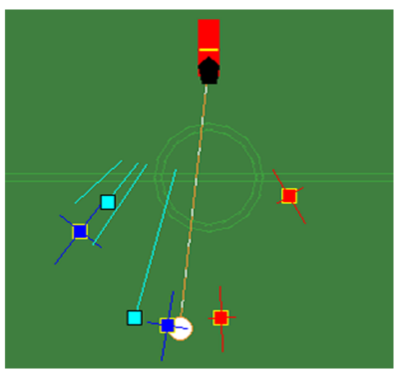
b) 

Fig. 5. An example with several robots. The large dots indicate the positions of the hypotheses. The lines through the dots illustrate the uncertainty of the estimations.

experiments included only standing robots due to a lack of adequate ground truth data for moving robots.

The implementation of this approach has already been applied to a dynamic scenario by the *Bremen Byters* team which built some tactical behaviors upon the computed robot estimations and used these in a RoboCup competition.

5 Conclusion and Future Works

In this paper, the authors have shown that it is possible to compute accurate position estimations of robots in the Four-Legged League. The low quality of information that is caused by the low perceptual capabilities of the AIBO robot may be compensated by applying sophisticated estimation techniques. The next step will be to create a complete world model that includes the positions of all robots on the field. Due to the limitations of a single robot, this has to be done by communicating information among the robots in a team. The local models described in this paper will be used as a foundation for such a global model.

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