Distributed Sensor Fusion for Object Position Estimation by Multi-Robot Systems

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Abstract—We present a method for representing, communicating and fusing distributed, noisy and uncertain observations of an object by multiple robots. The approach relies on re-parameterization of the canonical two-dimensional Gaussian distribution that corresponds more naturally to the observation space of a robot. The approach enables two or more observers to achieve greater effective sensor coverage of the environment and improved accuracy in object position estimation. We demonstrate empirically that, when using our approach, more observers achieve more accurate estimations of an object's position. The method is tested in three application areas, including object location, object tracking, and ball position estimation for robotic soccer. Quantitative evaluations of the technique in use on mobile robots are provided.

Index Terms—distributed sensing, multi-robot coordination

I. Introduction

Typically, individual robots can only observe part of their environment at any moment in time. In dynamic environments, information previously collected about currently unobservable parts of the environment grows stale and becomes inaccurate. Sharing information between robots can increase the effective instantaneous visibility of the environment, allowing for more accurate modeling (at whatever level) and more appropriate response. If it is processed effectively, information collected from multiple points of view can provide reduced uncertainty, improved accuracy and increased tolerance to single point failures in estimating the location of observed objects.

In order to meet the time demands of a highly dynamic environment (e.g. robotic soccer), the information transmitted between robots must be minimal and the computational demands to combine their observations must be minimal. Our approach makes use of a few easily obtainable parameters describing an observation and simple computations to meet these needs. We use two-dimensional statistical representations of target location observations generated by individual robots. These are combined independently on each robot to produce improved estimates of target locations

II. Background and Related Work

In Robotics, Kalman filters are frequently used to track objects or robot position over time. Smith and Cheeseman provide an overview and introduction to Kalman filter application and theory [13].

For object localization, Smith and Cheeseman use Kalman filtering to estimate error between different coordinate frames to determine the relative locations of objects [13]. Tang et al identify multiple objects using stereo, then predict future locations using a Kalman filter [14]. Wang et al use a Kalman filter to track objects in real-time and point a pan-tilt camera appropriately [15]. Petryk and Buehler use miniature electro-optical proximity sensors embedded in a robot's end effector with an extended Kalman filter to track individual objects before grasp [10].

For robot localization, Kalman filters are used to fuse odometry with sensor position estimates from sensors, such as sonar or vision. Sasiadek et al use extended Kalman filters to fuse odometry and sonar data [12]. Moreno et al use a sonar ring to observe projections of geometric beacons [8]. These are matched to an a priori map and merged with an extended Kalman filter to determine robot position. The technique is especially useful in dynamic applications such as robotic soccer. The CS Freiburg RoboCup team of Germany, for example, estimates position using odometry and by finding the field borders in laser range scans [3]. These two estimates are fused using a Kalman filter to localize the robots.

The ability to rapidly share distributed observations is critical in distributed dynamic tasks like robotic soccer. Most robot soccer team approaches use vision and/or sonar to localize and vision to locate objects in the environment. Some share information for planning and dynamic role assignment (ART [9]) and others share information to fill in blank areas in the world model (CS Freiburg [3,4], RMIT [1], 5dpo [2]).

The task we address is distinct from the others described above. We focus on fusing multiple simultaneous observations of the same object from distributed vantage points (as opposed to multiple observations from the same vantage point over instants in time). Our objective is to provide more accurate estimations of the location of objects that are simultaneously visible by multiple robots.

III. Fusing Gaussian Distributions

A. *Overview*

We represent a single observation of an object as a two-dimensional Gaussian distribution (Figure 1). The center, or mean of the distribution is the estimated location of the object and the standard deviations along the major and minor axes of the distribution correspond to estimates of the uncertainty (or noise) in the observation along each axis. The value of the distribution at any point corresponds to the probability that the object is actually in that location, given the observation.

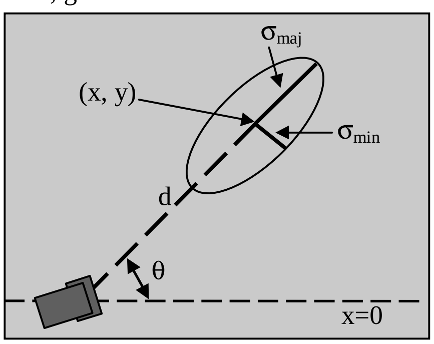

Figure 1. Gaussian distribution parameter definition: mean (x, y), angle of major axis θ, standard deviations along major and minor axes σ_{maj} and σ_{min}, distance to mean d.

Provided two observations are independent and drawn from normal distributions, the observations can be merged into an improved estimate with a linear Kalman filter. To meet cycle time requirements of a highly reactive system, an efficient method of combining distributions is necessary. We use a two-dimensional Kalman filter derived from Smith and Cheeseman's approach [13]. In their approach, two-dimensional Gaussian distributions can be combined using simple matrix operations. Because the result of merging two Gaussian distributions is itself a Gaussian, the operation is symmetric and associative and can be used to combine any number of distributions in any order.

Our approach, then, is to collect observations of multiple robots, (as in Figure 2), then merge the corresponding Gaussian distributions to yield a better estimate of the location and uncertainty of the observed object.

The canonical form of the two-dimensional Gaussian distribution depends on standard deviations, σ, a covariance matrix, C, and the mean, as shown [13]:

$$p(X) = \frac{1}{2\pi|C|} \exp\left(-\frac{1}{2} \left(X - \bar{X} \right)^T C \left(X - \bar{X} \right) \right) \qquad \text{Eq. 1}$$

where

$$C = \begin{bmatrix} \sigma_x^2 & \rho\sigma_x\sigma_y \\ \rho\sigma_x\sigma_y & \sigma_y^2 \end{bmatrix} \qquad \text{Eq. 1b}$$

The parameterization of the Gaussian in this representation does not correspond the parameters of our observations (Figure 1). We address the problem through a transformation of parameters from observation form to canonical form. In this form, the Kalman filter can be applied to merge the distributions. After the observations are merged, we extract the mean and standard deviations from the merged result (these correspond to the estimated location and uncertainty of the observed object).

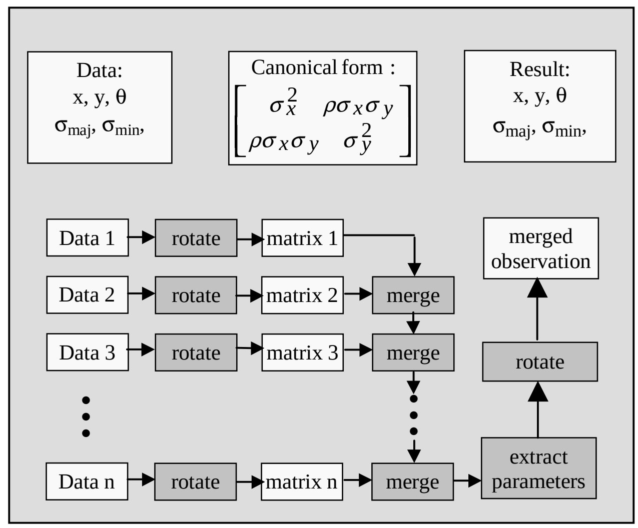

Figure 2. Block diagram representing the multi-distribution merging process. The multiplication step is conducted using the mathematical formulation described above. Each subsequent distribution is merged with the previous merging result.

B. *Mathematical Details*

We wish to determine the mean, standard deviations, and angle of the merged distribution to estimate object position and characterize the quality of the estimate. We compute the mean, standard deviations, and angle of measurement distributions sensor readings (mean and angle) and models of sensor error (deviations). Thus, we require a method of determining combined parameters from those of individual distributions.

The matrix form of Kalman filtering adopted by Smith and Cheeseman makes this computation relatively simple [13]. Because the mean, standard deviations, and orientation of the major axis are independent of scaling, they can be extracted from the merged covariance matrices without the need to consider scaling factors.

The covariance matrix of an observation, C, is initially determined from the major and minor axis standard deviations.

$$C = \begin{bmatrix} \sigma^2_{maj} & 0 \\ 0 & \sigma^2_{min} \end{bmatrix} \qquad \text{Eq. 2}$$

Since the observation may be oriented arbitrarily with respect to the global coordinate frame, it must first be rotated to align with this frame:

$$C = R(-\theta)^T C \ R(-\theta) \qquad \text{Eq. 3}$$

where θ is the angle of the distribution's principal axis with respect to the global x-axis. This rotation accomplishes the transformation from observation parameters to the canonical form. Once the observation is in the canonical form, we continue with Smith and Cheeseman's approach to merging.

The covariance matrices of two distributions is combined into a single covariance matrix representing the combined distribution:

$$C = C_1 - C_1 \left[C_1 + C_2 \right]^{-1} C_1 \qquad \text{Eq. 4}$$

The mean of the resulting merged distribution, X, is computed from the individual distribution means and covariance matrices.

$$\hat{X} = \hat{X}_1 + C_1 \left[C_1 + C_2 \right]^{-1} \left(\hat{X}_2 - \hat{X}_1 \right) \qquad \text{Eq. 5}$$

The angle of the resulting principal axis is obtained from the merged covariance matrix:

$$\theta = \frac{1}{2} \tan^{-1} \left(\frac{2B}{A - C} \right) \qquad \text{Eq. 6}$$

where A, B, and C represent the components of the covariance matrix (upper left, upper right/lower left, and lower right, respectively).

Lastly, the resulting major and minor axis standard deviations are extracted by rotating the covariance matrix to align with those axes:

$$C = R(\theta)^T C \ R(\theta) \qquad \text{Eq. 7}$$

and the resulting major and minor axis standard deviations can be directly computed from the covariance matrix by reversing Equation 2.

C. Simulated Example

Two robots at different locations observe a target object (Figure 3). Each observation produces a Gaussian distribution of possible locations for the object; typically, each distribution will provide greater accuracy along a different direction than the other distributions.

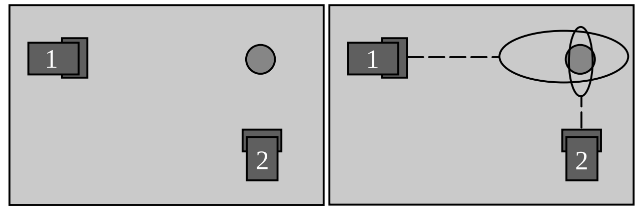

Figure 3. *Left:* Two robots see the target from different points of view. *Right:* Observations are gaussian; uncertainty increases with distance.

For this example, the robots are positioned with relative headings 90 degrees apart and looking directly at the target. The target is located at a position (10,10). The two simulated robot observations were drawn from a random normal distribution centered at the object's true position. The major and minor axis standard deviations of

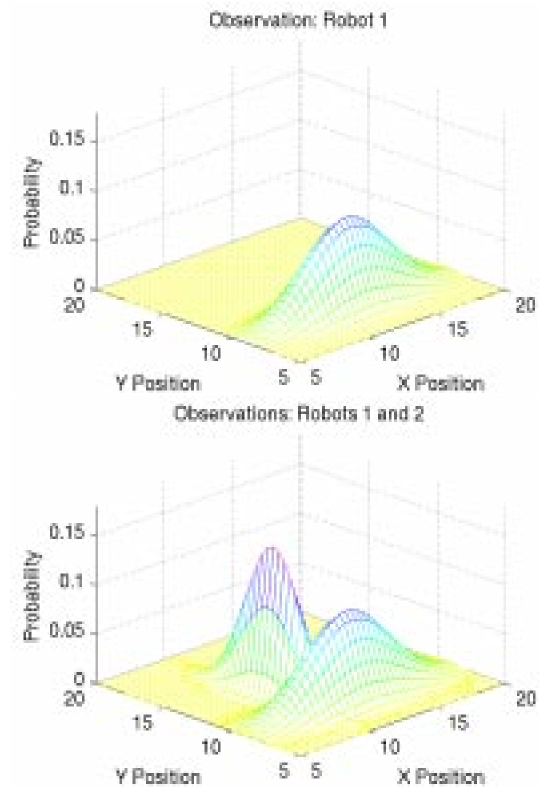

Figure 4. *Top:* Single robot observation distribution. *Bottom:* Two single robot observations to be merged.

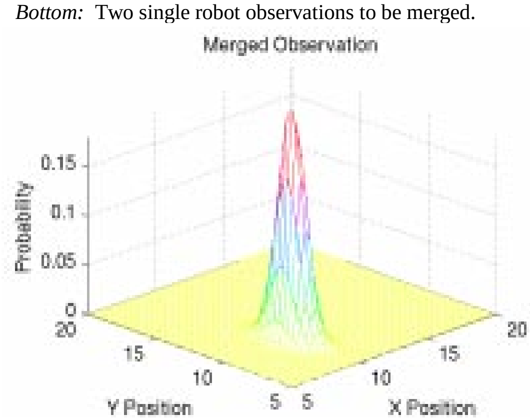

Figure 5. The resulting merged distribution, with smaller standard deviations (error) and higher accuracy in the mean.

these distributions were (5,3) for robot 1 and (3,1) for robot 2. Robot 1 reports a mean of (12.34, 9.02) and robot 2 reports a mean of (9.90, 11.69). In Figure 4, the distribution resulting from the single measurements by robot 1 and robot 2 are shown.

The result of merging distributions is shown in Figure 5. It is easily observed that the implied uncertainty is reduced, and the resulting distribution is centered more accurately relative to the actual target position. The merged mean is (9.97, 9.57), with major and minor axis standard deviations (0.89, 0.49).

IV. ASSUMPTIONS

Several assumptions are implicit in this approach. In addition to the assumption that sensor errors are independent and distributed normally, the robot coordinate frames are assumed to be coincident. Without this, data are incompatible and the merging is meaningless.

Several additional assumptions were introduced for simplicity in experimentation and camera calibration. First, the camera parameter calibration assumes that objects are at a known height from the ground plane; unknown objects are therefore assumed to be on the ground plane. This reduces the transformation from three dimensions to two. This is not a highly restrictive limitation, as common obstacles, agents, landmarks (etc) in environments are generally on the ground plane. Second, objects of interest are assumed to be unique in order to avoid the necessity of solving the association problem. Lastly, we assume robots to be perfectly localized; robot positional uncertainty is not taking into account in the generation of target location distributions. This assumption is only adopted for convenience, and the distributions could be easily grown to account for robot position uncertainty through convolution or other methods.

V. VALIDATION ON ROBOTS

A. *Hardware Platform*

The hardware platform used for the verification and other experiments is based on a Cye robot, an inexpensive and commercially available platform (Figure 6). This platform consists of a drive section and a trailer. The drive section uses differential drive with two wheels; the trailer is passive. On board the Cye is a motor controller processor. The Cye platform is equipped with a front bump sensor. An additional Pentium 266, running Linux, provides high level commands to the Cye computer and performs image processing. The algorithms to generate these high level commands and image processing are implemented in C and Java, using TeamBots software architecture. The addition of a wide field-of-view NTSC video camera provides the sensory input to the system. The image processing software performs color analysis and color blob detection and merging.

Figure 6. Enhanced Cye Robot platform.

For use on the hardware platform, camera calibration was conducted at two levels. First, *Flatfish*, a tool developed by Hans Moravec of Carnegie Mellon University, determined the parameters describing the aberrations of the lens. These parameters enable mapping from pixel location to points in three-space [7].

A second calibration step is used to characterize systemic errors. Targets are placed at a set of fixed distances and angles relative to the robot and the distance and angle calculated by the vision system is recorded. Comparing measured distance versus actual distance provides a mean bias as a function of measurement distance. After correcting measurements for this bias, proportional errors are determined.

A histogram of these sensing errors is provided in Figure 7. The figure indicates that the corrected distances are distributed approximately normally about the actual distance. From these errors, a standard deviation in distance can be directly determined. A similar process was completed for angle, though no bias correction was conducted. These deviations are used as parameters of the observation distributions.

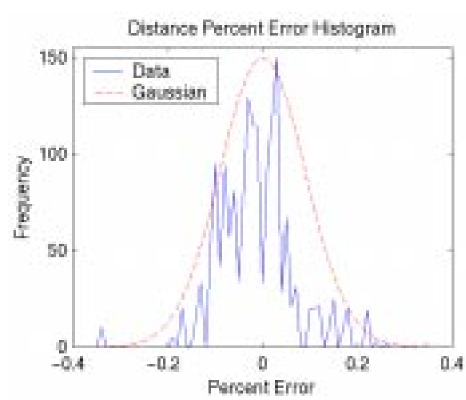

Figure 7. The histogram of distance error as a percent of distance is approximately Gaussian.

B. Experimental Setup

To test the approach, an experiment was devised in which three robots track an object through several sequential points in the environment. In this way, the accuracy of single-robot measurements can be directly compared to the accuracy obtained by combining data from two and three robots. An illustration of this experimental setup is shown in Figure 8; each robot is 1.5 meters from the origin of the coordinate frame.

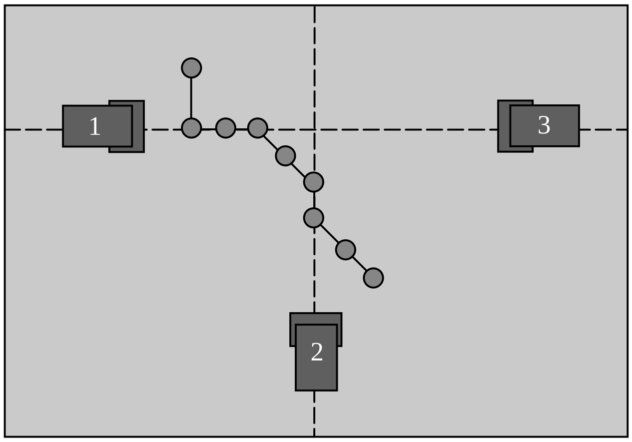

Figure 8. Experimental setup for validation. The line represents the ball trajectory with ball locations marked as circles. Dotted lines represent the global coordinate frame.

The ball was placed at a series of known discrete points along a trajectory. At each point, the location of the ball measured by each robot was recorded. These individual observations were merged in pairs and finally all combined.

C. Experimental Results

The experimental results are shown graphically in the following figures. In Figure 9, an example trajectory seen by an individual robot is compared to the actual path of the target. In the Figure 10, a merged result from two robots is similarly compared. The merged result from all three robots is shown in Figure 11.

In Figure 12 below, trajectory errors point-by-point and mean error are shown and compared for all single-robot, two-robot, and three-robot measurements.

While individual trajectories are sometimes accurate at single points, (in fact, occasionally slightly more accurate that the combined information) the consistency of accuracy shown in the combined results is absent in the single-robot trajectories. This is best characterized by plotting the mean error of single-robot observations, two-robot observations, and three-robot observations, as shown in Figure 13.

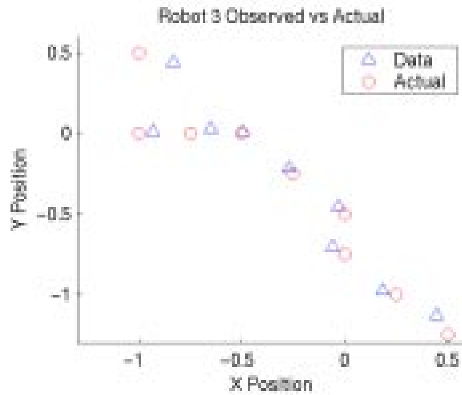

Figure 9. Observed ball trajectory reported by robot 3 compared to the actual ball trajectory.

Figure 10. Trajectory produced by merging observations of robots 2 and 3 compared to actual trajectory. Notice improvement in lower right.

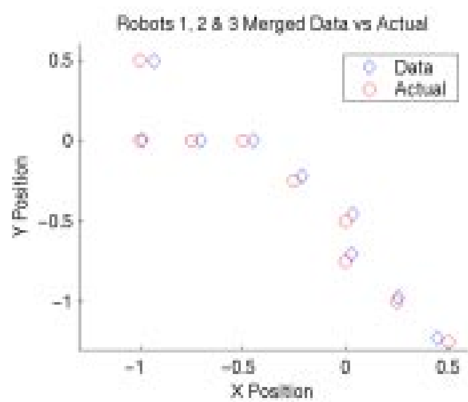

Figure 11. Trajectory produced by merging observations of robots 1, 2 and 3 (diamonds) compared to actual ball trajectory (circles). Notice further improvement in upper left.

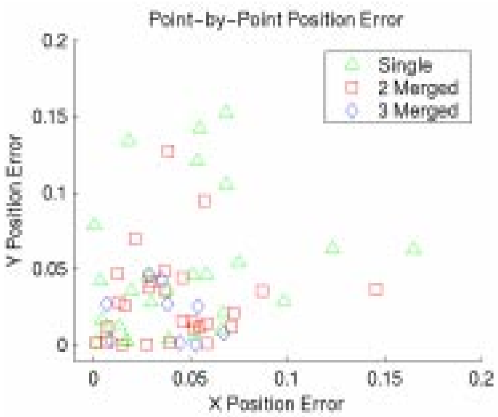

Figure 12. Position error in x and y for each measurement. Successive merging further lowers bounds on position error and reduces outlier frequency.

Figure 13. Mean position error in x and y over all single observations, all data merged from 2 observations, and all data merged from 3 observations. Each successive merging reduces mean error.

VI. TEST APPLICATIONS AND RESULTS

A. Location and Retrieval of Unseen Targets

This test application for this method demonstrates the ability to increase the effective field of view of agents. In this experiment, one robot is positioned so that it can see, but not reach, the target object. The other robot cannot initially see the target object, even with camera panning, but the path to the object is unobstructed (Figure 14).

By sharing visual information, the unobstructed robot immediately obtains a target location without requiring random search. The robot is able to successfully locate the object using information provided exclusively by the second robot. Once the object is located, it effectively reaches and manipulates the target using the merged position provided by both robots. Due to the small distances traveled from precisely known starting positions, the assumptions on robot localization and coordinate frames hold. The target was never allowed to leave the ground plane.

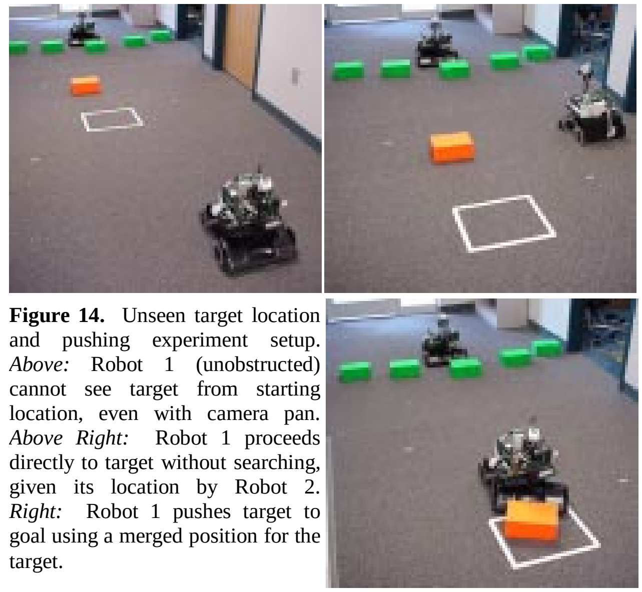

Figure 14. Unseen target location and pushing experiment setup. *Above:* Robot 1 (unobstructed) cannot see target from starting location, even with camera pan. *Above Right:* Robot 1 proceeds directly to target without searching, given its location by Robot 2. *Right:* Robot 1 pushes target to goal using a merged position for the target.

B. Blind Robot Target Tracking

In this experiment, three robots were positioned around a target area. For convenience these robots were positioned at relative headings of 90 degrees. A target was moved throughout the target area, and all three robots tracked the ball using the position obtained by merging all three observations. One of the robots was subsequently blindfolded covering the camera with a box (Figure 15).

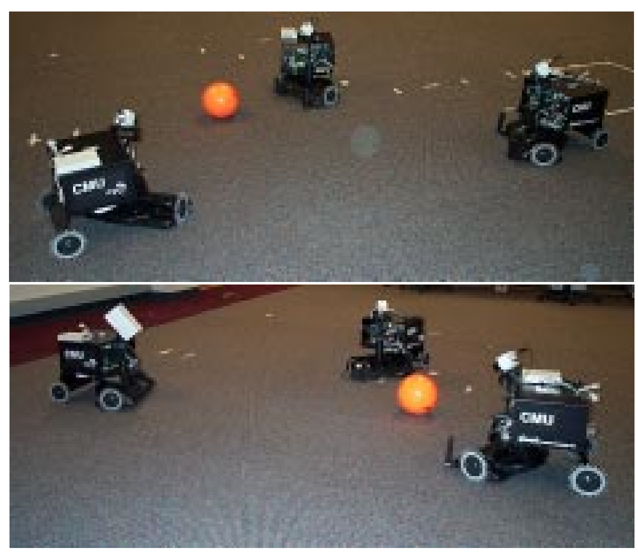

Figure 15. Blind robot ball tracking experiment setup. *Above:* In this experiment, three robots track the ball with at a location generated by combining all three observations. *Below:* In this experiment, a robot is blinded (for example, a box covers the left robot's camera) and it still successfully tracks the ball with combined data from the remaining two.

The ability of the blinded robot to track the ball using the merged position from the other two, was not substantially diminished. The robots were able to track the target, even at higher speeds, in most cases and always quickly recovered the object when lost. Even when the target traveled within the line of sight of a single robot (with diminished accuracy in this dimension), the additional point of view could make up for this accuracy. As robot positions are precisely known and fixed, the assumptions on robot localization and coordinate frames also hold here.

C. Robot Soccer

This approach to distributed sensing was applied to the CMU Hammerheads 2000 RoboCup middle-sized team (Figure 15). At each cycle, robots would transmit the position of the ball, if visible, so that it could be combined with all other current observations. Widely conflicting observations (for example, those with means differing by at least 2 standard deviations) were not merged. This eliminates confusion resulting from false targets (or more generally, multiple targets) and data collected in incompatible coordinate frames. This, in theory, would provide robots far from the ball with more accurate positions and allow robots that could not see the ball to quickly locate it.

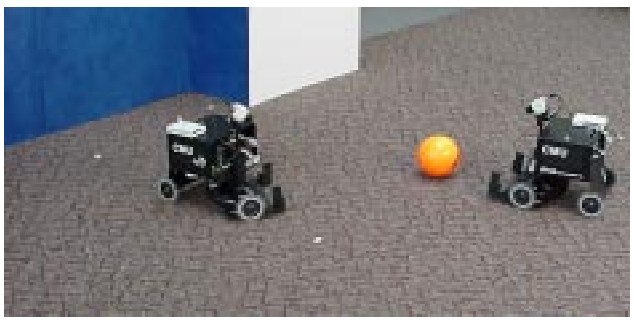

Figure 16. A test run of robot soccer. Attacker (right) attempts to score on blue goal defender (left).

The CMU Hammerheads 2000 team robots were localized entirely by on-board odometry. This odometry drifts over time, leading to differences in coordinate frames. As a result, the primary impact of distributed sensing was to provide a starting point for robots to locate balls that had become invisible. This use of shared information did allow robots to more quickly locate a lost ball during competition when it was not entirely obstructed. Despite the discrepancy in coordinate frames, the coordinate frames were generally coherent enough that when a robot looked at a potential target position, the ball became visible within the camera's wide field of view.

VII. Conclusions

We present a method for using a simple representation of two-dimensional Gaussian distributions to fuse target position estimates from two or more robot agents. This approach is based on accepted Kalman filter theory and implements real-time sensor data fusion on a reactive multi-robot system for several different applications. The successful ability to fuse these statistical measurements and the ability to receive position estimates on targets not visible allows our robots to quickly acquire targets and to more accurately estimate object position. While this work is used vision for sensing, the approach can be applied to any sensor or suite of sensors which can be modeled by approximately Gaussian distributions.

This approach to distributed sensing and information sharing is very promising based on the applications presented here: unseen target location, accurate target acquisition and manipulation, and robot soccer. However, several extensions of this work are necessary for practically implementing this method of distributed sensing and information sharing. Even in well-localized systems, disparity between coordinate frames can arise. Such disparity must be accommodated and/or corrected. Autonomous re-merging of coordinate frames using sensors will be investigated. Additionally, well-localized robots still maintain some uncertainty in position, as computed by the localization. The accommodation of robot positional uncertainty will be incorporated into the target position distributions. Lastly, it may be possible to remove the restriction that objects of unknown size are on the ground plane; this involves a different method of transforming pixel location into world coordinates and requires further research.

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