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Object Tracking for Calibration of Distributed Sensors in Intelligent Space

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1. Introduction

In recent years, the research field on smart environments, which are spaces with multiple embedded and networked sensors and actuators, has been expanding (Cook & Das, 2004). The main purpose for the introduction of smart environments is to support humans in both physical and informative ways (Johanson et al., 2002), (Mynatt et al., 2004), (Mizoguchi et al., 1999). In smart environments, the distributed sensor nodes observe the spaces, extract useful information from the obtained data and the actuators including mobile robots provide various services to users. Moreover, robots in the space can get necessary information from the smart environment and operate without restrictions due to the capability of on-board sensors and computers. In fact, mobile robot control is easier in smart environments since the global positions can be directly measured by using distributed sensors and Simultaneous Localization And Mapping (SLAM) problem (Durrant-Whyte & Bailey, 2006), where the robot tries to simultaneously estimate its own location and build a map of the environment, can be completely avoided (Lee & Hashimoto, 2003).

However, one of the major problems in developing smart environments is calibration of the sensors. Calibration is needed for proper calculation from the local (sensor's) coordinate system to the world (smart environment's) coordinate system and it is usually done by using calibration objects that are objects with known positions, shapes and so on. For example, researches on camera calibration based on geometrical features including 3D points (Tsai, R. Y., 1987), 2D points (Sturm & Maybank, 1999), (Zhang, 2000), lines (Zhang, 2004), circles (Wu et al., 2004), and spheres (Agrawal & Davis, 2003) are being pursued actively. Several researchers extended such a single camera calibration algorithm to a multiple-camera calibration algorithm. An extension of a planar point pattern based calibration algorithm to the multi-camera systems with an arbitrary number of cameras is presented in (Ueshiba & Tomita, 2003). The algorithm is based on factorization of homography matrices between the model and image planes, which is expressed as a composition of a camera projection matrix and a plane parameter matrix. If a calibration object is put in three or more places, the relative positions and orientations between cameras as well as the intrinsic camera parameters are determined. Another work also utilized a known 2D calibration object for stereo camera calibration (Malm & Heyden, 2001). The technique uses both stereo camera constraints and single camera constraints, and therefore noise-robust calibration is realized.

In the case of smart environments, it takes a great deal of time and efforts to calibrate the sensors since multiple sensors are distributed in the space. Although the researches

mentioned above aim to lighten this enormous work, our research purpose is to automate the calibration process with satisfactory accuracy. In order to solve this problem, mobile robots have been used for realizing automated calibration. Mobile robots can cover wide areas of the environment by moving from place to place so there is no need to place many landmarks in exactly known positions beforehand. Some researchers focus on node localization in wireless sensor networks using mobile robots (Shenoy & Tan, 2005), (Sreenath et al., 2006). In the methods, each mobile robot broadcasts its position information and if a wireless sensor node can get the information, the node is considered to be located adjacent to the robot. An effective path planning of mobile robots for wireless node localization is also addressed in (Koutsonikolas et al., 2006). Although the sensor nodes just receive the position information from the robots in these researches, the measurement of the sensors can also be used for calibration. In (Rekleitis & Dudek, 2005), which is closely related to our work shown in this chapter, camera sensor network is calibrated based on grid patterns attached to a mobile robot. We also introduce a mobile robot assisted calibration method and use the position information of the robot to calibrate distributed sensors including laser range finders and cameras. Hereby we can add a calibration function without major changes in the system because we can use existing moving object tracking and mobile robot localization functions of smart environments.

Next section gives a brief introduction of our smart environment which is called "Intelligent Space (iSpace)." Section 3 and 4 describe the automated calibration method based on the mobile robot tracking for distributed laser range finders and cameras, respectively. Mobile robot localization used in the calibration method is explained in section 5. Experimental results of the proposed method and comparison with the manual calibration are shown in section 6. Finally, a conclusion is given in section 7.

2. Intelligent space

"Intelligent Space (iSpace)" has been proposed by Hashimoto laboratory at The University of Tokyo (Lee & Hashimoto, 2002). Figure 1 shows the concept of iSpace. We call the sensor node devices distributed in the space DINDs (Distributed Intelligent Network Device). A DIND consists of three basic components: sensors, processors and communication devices. The processors deal with the sensed data and extract information about objects (type of object, three dimensional position, etc.), users (identification, posture, activity, etc.), and the environment (geometrical shape, temperature, emergency, etc.). The network of DINDs can realize the observation and recognition/understanding of the events in the whole space. Based on the extracted and fused information, actuators such as displays or projectors embedded in the space provide informative services to users. In iSpace, mobile robots are also used as actuators to provide physical services to the users and for them we use the name mobile agents.

Figure 2 shows a configuration of the iSpace implementation in our laboratory. CCD cameras, laser range finders, and a 3D ultrasound positioning system are used as sensors of DINDs. The laser range finders are placed close to the ground horizontally (about 20 cm above the floor). The advantage of the low position is that it is possible to scan also relatively short objects, assuring that all objects on the floor will enter the scan. The 3D ultrasound positioning system involves 112 ultrasonic receivers installed on the ceiling. This system can measure the three dimensional position of an ultrasonic transmitter (tag) to an

accuracy of 20-80 millimeters using triangulation. Moreover, differential wheeled robots are used as mobile agents. For estimating the position and orientation of the robot, an ultrasonic transmitter is installed on the top of the mobile robot. The mobile robot is also equipped with a wireless network device to communicate with iSpace.
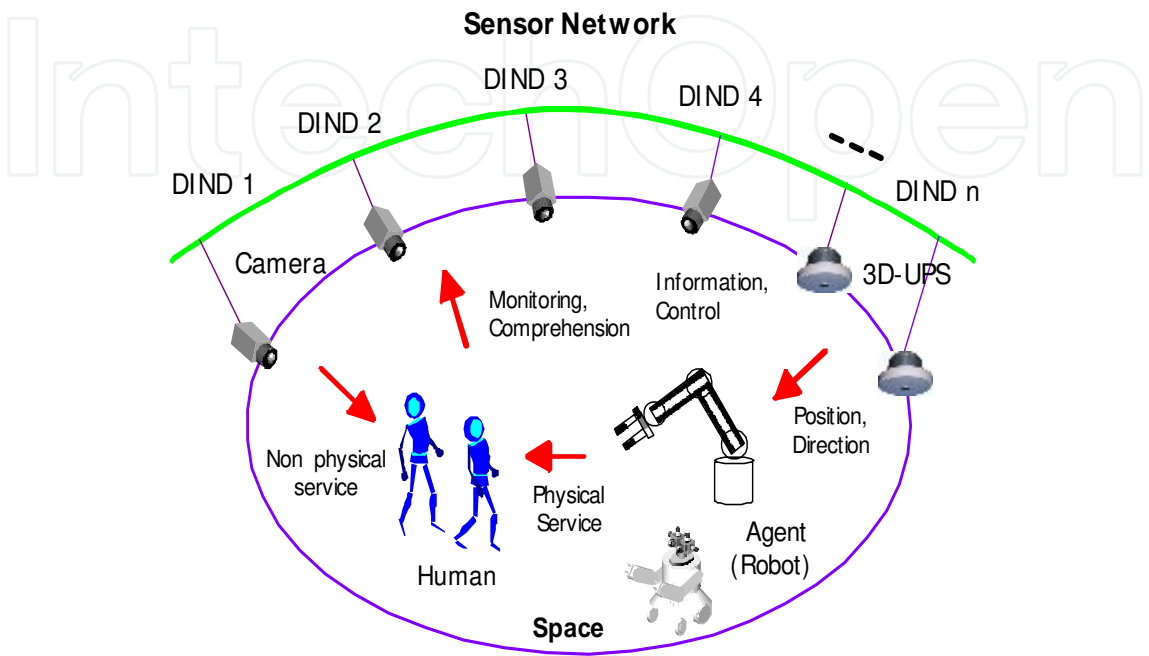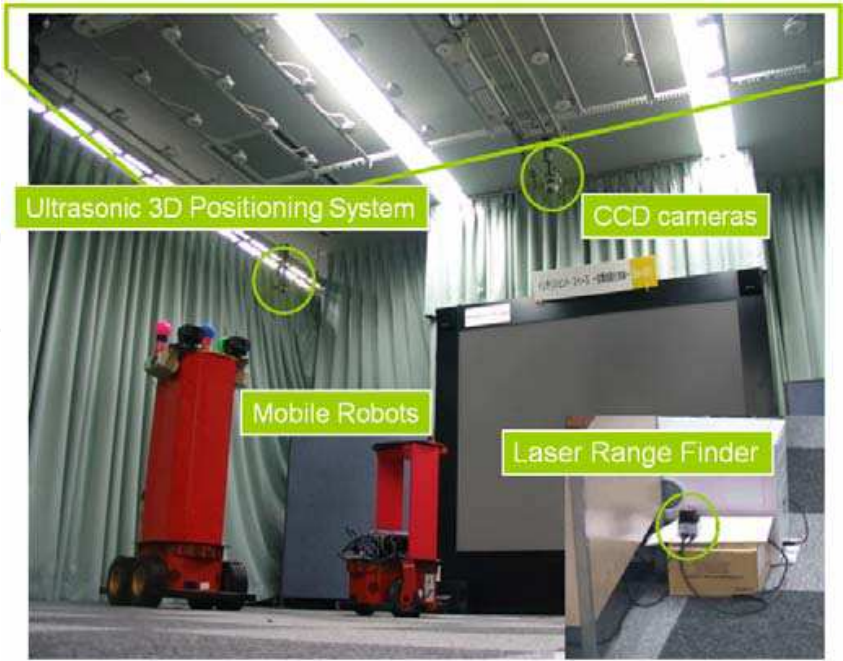

Fig. 1. Concept of Intelligent Space (iSpace)

Fig. 2. Configuration of Intelligent Space – sensors and mobile robots

3. Automated calibration of distributed laser range finders

3.1 Overview of the method

Our goal is to find transformation parameters (translation vector T and rotation matrix R) from the laser range finder coordinates to the world coordinates. Since the laser range finders are placed horizontally as noted in section 2, the calibration parameters are position and orientation of the laser range finder in 2D plane (T^i_{xg}, T^i_{yg}, θ^i_g) (i=1, 2, ..., N), where N and i denote the number of laser range finders in the environment and index of each laser range finder, respectively. As mentioned in section 1, we utilize mobile robots in iSpace to realize the automated calibration. Figure 3 shows the overview of the calibration method.

Let $^WO{-}^Wx^Wy$ be the coordinate system fixed to iSpace (world coordinate system) and $^{Li}O{-}^{Li}x^{Li}y$ be the coordinate system fixed to the ith laser range finder (laser range finder i coordinate system). First, each DIND tracks the mobile agents and gets the position of the mobile robots in the local coordinate system (x^i_k, y^i_k). The DINDs also request the position server in iSpace where the postion information of objects is collected and stored to send the position of the robot in the world coordinate system (x^g_k, y^g_k). The calibration process is then performed based on the set of corresponding points $\{(x^g_k, y^g_k), (x^i_k, y^i_k)\}$ (k = 1, 2, ..., n).
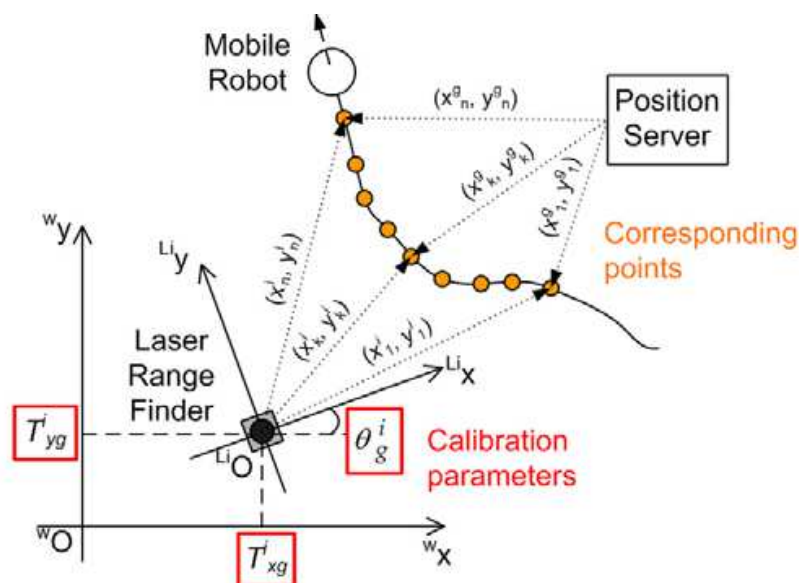

Fig. 3. Calibration of a laser range finder using a mobile robot

In the following subsections, the functions needed for the proposed calibration method are described. Tracking of moving objects and pose estimation from a set of corresponding points are explained in section 3.2 and 3.3, respectively.

3.2 Object tracking using a laser range finder

The tracking process consists of extraction of objects, estimation of the object centers and tracking using Kalman Filter.

Figure 4 shows the the object extraction. In the extraction process, background subtraction is first applied. The static parts of scan (background) are subtracted from the scan data in order for determining which parts of the scan are due to moving objects (foreground). The scan points in the foreground are then clustered based on the Euclidean distance between them using a nearest neighbor classifier. This divides the foreground to a number of

clusters, each belonging to one of the tracked objects. Clusters with a small number of scan points are discarded as measurement noise. Data association is based on the Euclidean distance. The position of cluster centers are compared with the positions of currently tracked objects and each cluster is assigned to the closest object. The clusters that are far from all currently tracked objects are considered as new objects, and a new tracking process is started for them.

From the previous step the positions of cluster centers were obtained. But since the objects are scanned from one side, the center of the obtained cluster of points (x_{cl}, y_{cl}) in general does not coincide with the center of the tracked object (x_{obj}, y_{obj}). So, as shown in Fig. 5, the object center is assumed to be at a fixed distance d from the center of the cluster of scan points belonging to it, that is,

$$x_{obj} = x_{cl} + d\cos(\alpha)$$
$$y_{obj} = y_{cl} + d\sin(\alpha)$$

(1)

where α is the angle of the line between the laser range finder and the center of the cluster, and d is a parameter depending on the radius of the object. In our experiments d was set to 6 centimeters for human (i.e. human's leg) and 15 centimeters for the mobile robot.
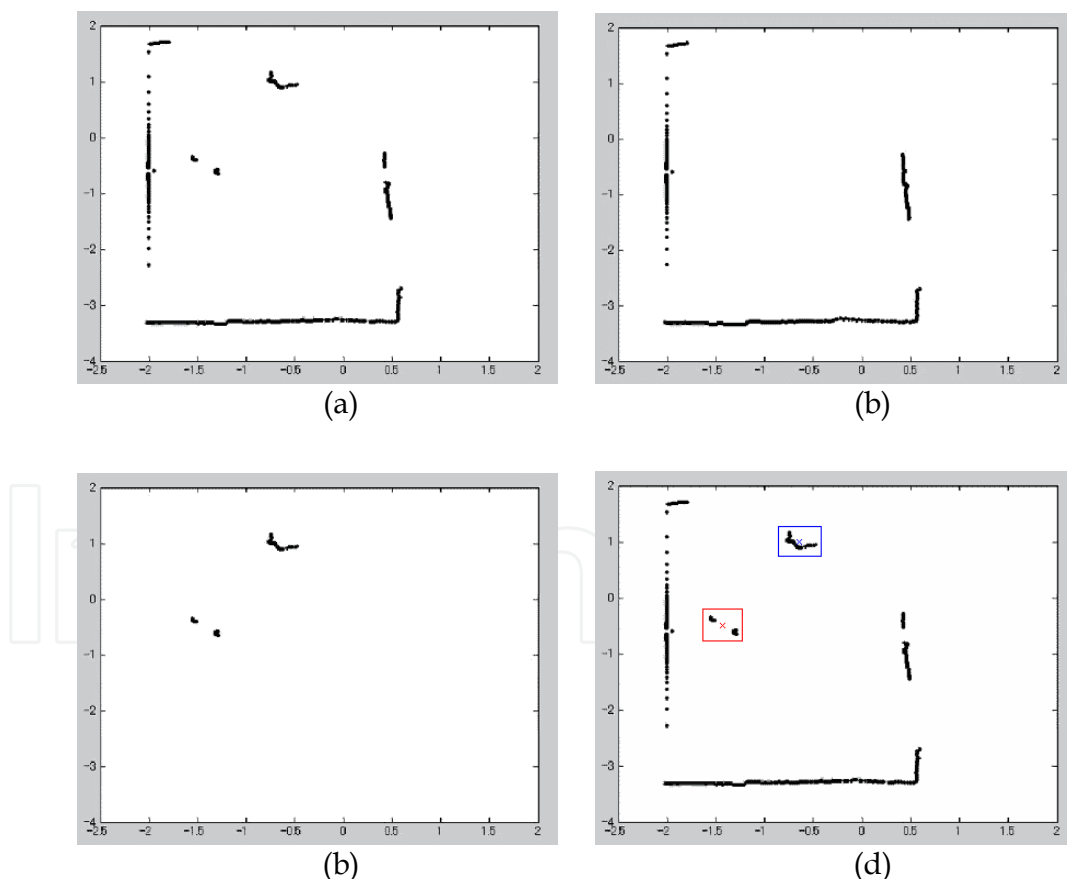

Fig. 4. Process of object extraction using laser range finder (a) raw scan data, (b) static part of the scan (background), (c) result of background subtraction (foreground), (d) result of clustering and centers of the clusters. The units of x and y are in meters.
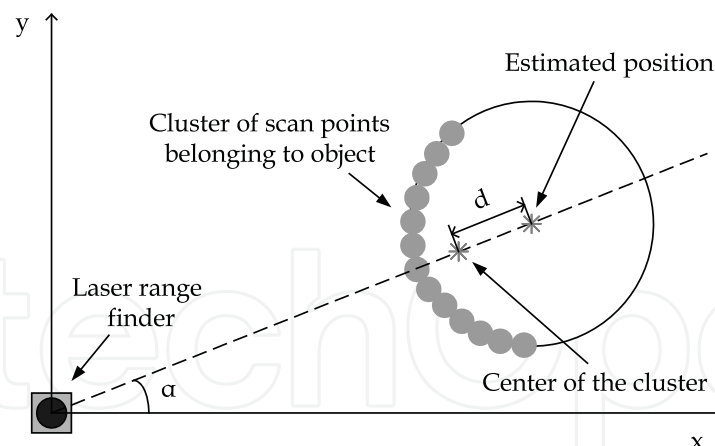
Fig. 5. Estimation of object center

Moreover, in order to distinguish between humans and mobile robots, the number of clusters belonging to an object is used since two clusters belonging to his/her legs are detected in the case of tracking a human. In our implementation we gradually determine the type of object by filtering the number of clusters. Only the positions of mobile robots are used for calibration purpose.
Finally, the Kalman filter is applied to track the objects.
The details of our laser range finder based tracking method and evaluation of the method are described in (Brscic & Hashimoto, 2006).

3.3 Calibration of laser range finders based on the corresponding points
In the calibration process, the position and orientation of the laser range finders in the world coordinate system (T^i_{xg}, T^i_{yg}, θ^i_g) is calculated. We solve the least square error problem denoted by the following equation:

$$\varepsilon^2 = \sum_{k=1}^{n} \left((x^g_k - \cos\theta^i_g x^i_k + \sin\theta^i_g y^i_k - T^i_{xg})^2 + (y^g_k - \sin\theta^i_g x^i_k - \cos\theta^i_g y^i_k - T^i_{yg})^2 \right) \tag{2}$$

where the indices g and i represent the obtained global and local coordinates respectively. If more than one set of corresponding points are obtained, we can derive the following estimates from $\dfrac{\partial\varepsilon^2}{\partial T^i_{xg}} = 0$, $\dfrac{\partial\varepsilon^2}{\partial T^i_{yg}} = 0$, and $\dfrac{\partial\varepsilon^2}{\partial\theta^i_g} = 0$:

$$T^i_{xg} = \mu^g_x - \cos\theta^i_g \mu^i_x + \sin\theta^i_g \mu^i_y \tag{3}$$

$$T^i_{yg} = \mu^g_y - \sin\theta^i_g \mu^i_x - \cos\theta^i_g \mu^i_y \tag{4}$$

$$\theta^i_g = \operatorname{atan2}\left(\sum_{k=1}^{n} \frac{-\left(x^g_k y^i_k - y^g_k x^i_k\right)}{n} + \mu^g_x \mu^i_y - \mu^g_y \mu^i_x , \right.$$
$$\left. \sum_{k=1}^{n} \frac{\left(x^g_k x^i_k + y^g_k y^i_k\right)}{n} - \mu^g_x \mu^i_x - \mu^g_y \mu^i_y \right) \tag{5}$$

where atan2($\cdot$) denotes the four-quadrant inverse tangent function and μ's stand for mean values, for example:

$$\mu_x^g = \frac{1}{n} \sum_{k=1}^{n} x_k^g \qquad (6)$$

The problem with least-squares estimation as given by equations (3)-(5) is sensitivity to outliers. Since robot tracking is done online it is possible that outliers, such as miscorrespondence between data can easily appear. In order to eliminate the effect of outliers instead of simple least squares we use the least median of squares (LMedS) based estimation. In the LMedS method, the estimation error is evaluated by not the sum of the square error but its median value.

The automated calibration process is summarized as follows:
1. Store corresponding points (xg_k, yg_k), (xi_k, yi_k) acquired by the robot tracking process
2. Sample 2 data randomly from the set of corresponding points
3. Calculate (T^i_{xg}, T^i_{yg}, θ^i_g) from the sampled data using equations (3)-(5)
4. Evaluate the estimation error by the median of the square error for all corresponding points
5. Repeat steps 2) – 4) enough times
6. Select (T^i_{xg}, T^i_{yg}, θ^i_g) which has minimum estimation error as the estimate

4. Automated calibration of distributed cameras

4.1 Overview of the method
The idea of the automated camera calibration is similar to the one explained in the previous section. Two measurements, the result of robot localization and the tracking result of the robot, are stored as corresponding points and the calibration is performed based on them. But, in this case, the position information obtained by a camera is the positions of the robots on the image plane. In addition, we need to calibrate both the intrinsic and the extrinsic camera parameters.

In the following subsections, tracking of mobile robots using a camera is explained in section 4.2 and the calibration method is mentioned in section 4.3.

4.2 Visual tracking of mobile robots
To detect moving objects in iSpace using CCD cameras, a similar algorithm to the one using laser range finders is implemented. In addition, we utilize color markers installed on a mobile robot to identify the mobile robot. Since color histogram is stable to deformation and occlusion of the objects relatively (Swain & Ballard, 1991), it is qualified as unique feature value to represent each object. Compared with the contour and so on, color histogram of the object stays largely unchanged against the various images that are captured by the distributed cameras.

Following three processes are performed to detect color markers.
1. Background subtraction: The background subtraction process compares the current image frame and an adaptive background image frame to find parts of the image that have changed due to the moving object.

2. Color histogram matching: The color histogram matching process searches over the current image and finds target colors which are registered in advance.
    In the previous processes, the system does not discriminate if each feature point belongs to the color marker or is just noise. So we need the following segmentation process to detect target objects and remove noise.
3. Segmentation: The overlapped areas of results from both background subtraction and color histogram matching are clustered. Clustering algorithm is based on nearest neighbor method. If the distance in both the x and y direction between two pixels is lower than a given threshold, these pixels are considered as part of the same object. In case that the number of pixels, height or width of the cluster does not get to a certain value, the cluster is removed as noise.

Figure 6 (left) and (right) show a captured image and the result of the color marker detection, respectively. We can find that three color markers on the top of the mobile robot are detected successfully.
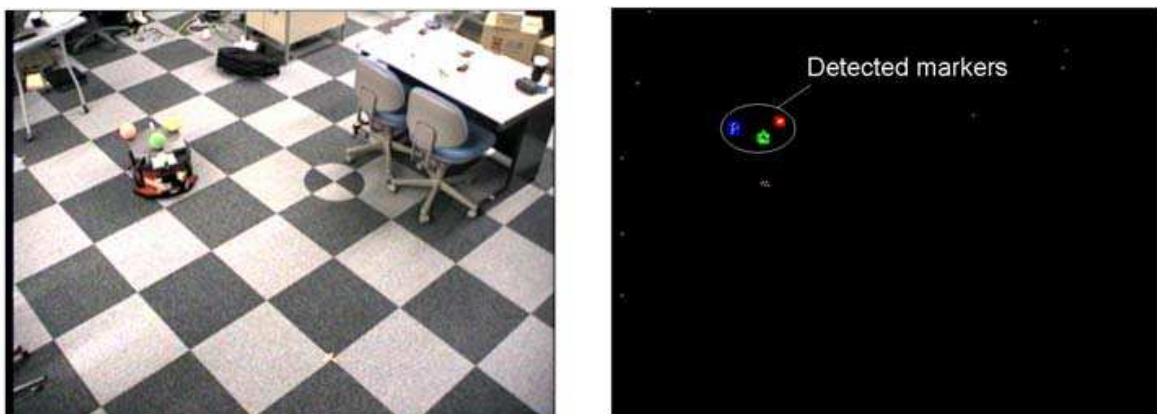

Fig. 6. Detection of color markers on a mobile robot using a camera DIND

4.3 Calibration of cameras based on the corresponding points

The automated camera calibration is performed based on the positions of the robots in the world coordinate system (xg_k, yg_k) and their corresponding points in the image coordinate system (u^i_k, v^i_k) ($k = 1, 2, ..., n$). Here we apply Tsai's method (Tsai, 1987) for the calibration. Although the method requires a 3D calibration object, we can use mobile robots with different heights or multiple markers attached to different heights.

In the Tsai's method, following 11 parameters are calibrated.

Five intrinsic parameters are:

* f: effective focal length
* κ_1: 1st order lens distortion coefficient
* s_x: uncertainty scale factor for x
*   (C_x, C_y): computer image coordinate for the origin in the image plane

Six extrinsic parameters are:

* R_x, R_y, R_z: rotation angles for the transform between the world and camera coordinate frames
* T_x, T_y, T_z: translational components for the transform between the world and camera coordinate frames

5. Mobile robot localization

In calibration methods based on corresponding points shown in section 3 and 4, the position information of robots in the world coordinate system is required. In our mobile robot localization method, the position of the mobile robot measured by the 3D ultrasonic positioning system installed in the space and the mobile robot on-board sensor data (wheel encoder) are fused to minimize the position error. In the following subsections, the detail of the localization method is given.

5.1 Model of the mobile robot

We consider a two-wheeled mobile robot model shown in Fig. 7. Let $^WO\text{-}^Wx^Wy$ be the coordinate system fixed to iSpace (world coordinate system) and $^RO\text{-}^Rx^Ry$ be the coordinate system fixed to the mobile robot (robot coordinate system). The position and orientation of the mobile robot are denoted by (x, y, θ) in the world coordinate system. The control inputs for the mobile robot are the translational velocity v and rotational velocity ω. Here, the kinematic model for the mobile robot is expressed as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \cos\theta & 0 \\ \sin\theta & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} \tag{7}$$
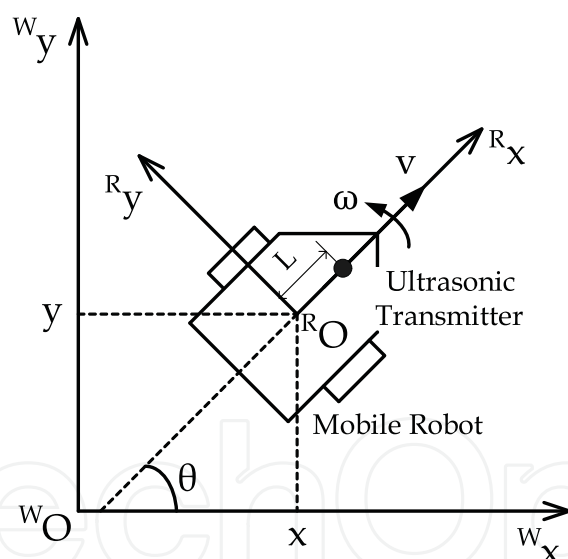

Fig. 7. Model of a mobile robot

In addition, an ultrasonic transmitter used with the ultrasonic positioning system is installed on the mobile robot. Its coordinate in the robot coordinate system is $(L, 0)$.

5.2 Localization using extended Kalman filter

The position and orientation of the mobile robot are estimated based on data from iSpace (the 3D ultrasonic positioning system) and the mobile robot (wheel encoder). These two measurement data are fused using extended Kalman filter. Extended Kalman filter has been widely applied to sensor fusion problems and it is computationally-efficient compared to other probabilistic methods, e.g. particle filter (Thrun et al., 2005).

In order to implement the extended Kalman filter, the model of the system has to be developed. Discretizing (7), we obtain the following state equation:

$$\begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + v\Delta t \cos\theta_{k-1} \\ y_{k-1} + v\Delta t \sin\theta_{k-1} \\ \theta_{k-1} + \omega\Delta t \end{bmatrix} + \mathbf{W}_k w_k \tag{8}$$

where x_k, y_k and θ_k denote position and orientation of the mobile robot at time k, Δt is the sampling rate, v and ω are the translational velocity and the rotational velocity obtained from encoders, w_k represents the process noise.

The observation equation is expressed as follows:

$$\begin{bmatrix} x_{zps} \\ y_{zps} \end{bmatrix} = \begin{bmatrix} x_k + L\cos\theta_k \\ y_k + L\sin\theta_k \end{bmatrix} + \mathbf{V}_k v_k \tag{9}$$

where (x_{zps}, y_{zps}) is the position of the ultrasonic transmitter in the world coordinate system observed by iSpace and v_k represents the measurement noise. L is the distance on the central axis between the tag and robot center, as noted in Fig. 7.

Linearizing the state equation, Jacobian matrix A_k is obtained:

$$\mathbf{A}_k = \begin{bmatrix} 1 & 0 & -v\Delta t \sin\theta_{k-1} \\ 0 & 1 & v\Delta t \cos\theta_{k-1} \\ 0 & 0 & 1 \end{bmatrix} \tag{10}$$

We consider that the noise on the encoder is white noise with a normal distribution. Here, the matrix W_k is expressed as follows:

$$\mathbf{W}_k = \begin{bmatrix} -\Delta t \cos\theta_{k-1} & 0 \\ -\Delta t \sin\theta_{k-1} & 0 \\ 0 & -\Delta t \end{bmatrix} \tag{11}$$

From the observation equation, the matrix H_k is

$$\mathbf{H}_k = \begin{bmatrix} 1 & 0 & -L\sin\theta_k \\ 0 & 1 & L\cos\theta_k \end{bmatrix} \tag{12}$$

The matrix V_k is determined as follows:

$$\mathbf{V}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{13}$$

In this research, we assume the process noise covariance Q and measurement noise covariance R are constant and use diagonal matrices. The values are tuned experimentally.

6. Experiment

6.1 Calibration of distributed laser range finders

In the environment shown in Fig. 8, three laser range finders are calibrated using a mobile robot. The arrangement of the laser range finders and the actual path of the mobile robot,

which is estimated by the mobile robot localization method described in the previous section, are also shown in the figure. The mobile robot entered the room from the right part of Fig. 8 and circled around the room in clockwise direction. In the mobile robot navigation system installed in iSpace, to find the best way for the robot to move through the space towards goals (path planning), the Field D* method (Ferguson & Stentz, 2005) is used. Moreover, in order for the robot to follow the calculated path and at the same time avoid bumping into obstacles, the Dynamic Window Approach (DWA) (Fox et al., 1997) is applied as a local control algorithm.
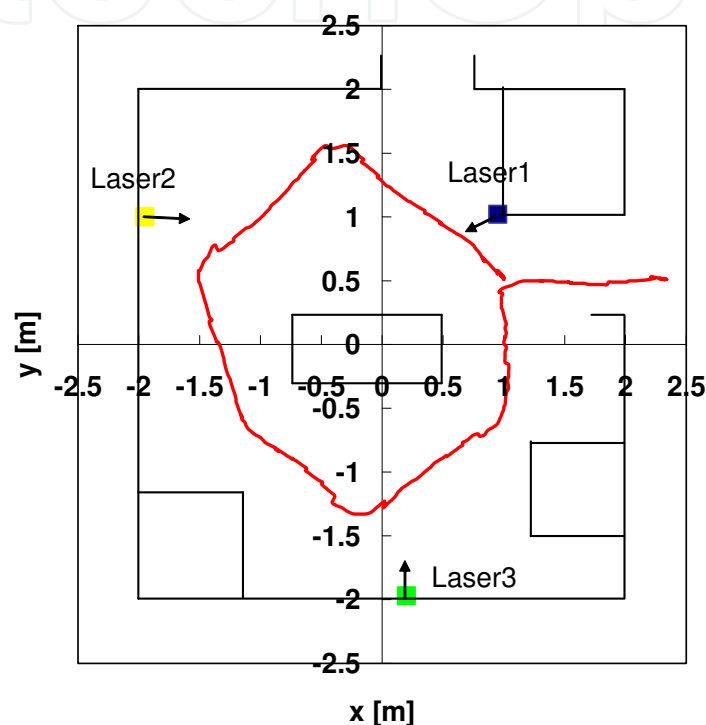
Fig. 8. Experimental environment for calibration of laser range finders – arrangement of the sensors and path of the mobile robot estimated by the extended Kalman filter

In order to evaluate the accuracy of the proposed method, we make a comparison between the automated calibration and manual calibration. In the case of manual calibration, a calibration object (an object which can be well detected by a laser range finder) is placed in turn on several points with known global coordinates and the calibration parameters are calculated by (3)–(5).

Table I shows the result of the automated calibration compared to that of manual one. The maximum difference between manual calibration and automated calibration is 0.11 meters for translation and 0.06 radians for rotation. The laser range fingers can only measure the edge of the mobile robot, but the tracking process works well and almost the same result as manual calibration case is achieved. The tracked positions of the mobile robot in each sensor node, which are transformed into the global coordinates using the estimated parameters are shown in Fig. 9. It is obvious that there is a good correspondence between the tracks, which shows that the calibrated parameters are correct.

LRF ID	Automated / Manual		
i	T^i_{xg} [m]	T^i_{yg} [m]	θ^i_g [rad]
1	−1.91 / −1.95	1.10 / 1.00	−0.19 / −0.15
2	0.99 / 0.95	0.95 / 1.02	−2.60 / −2.54
3	0.09 / 0.20	−2.01 / −1.97	1.56 / 1.60

Table 1. Estimated pose of the distributed laser range finders - comparison of automated and manual calibration results
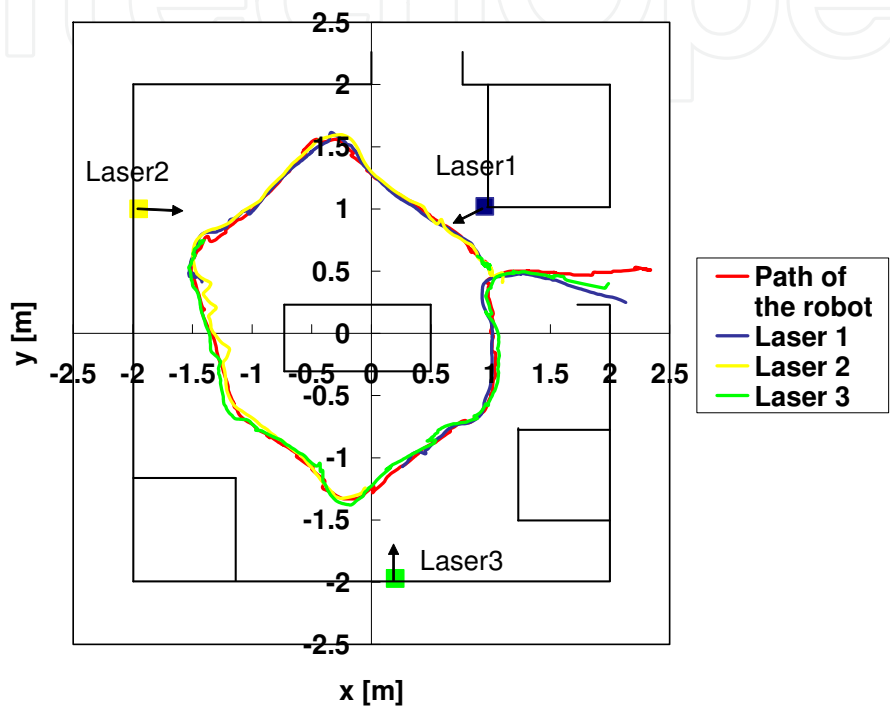

Fig. 9. The actual path of the mobile robot (presented again) and the tracked positions of the robot in each sensor node, obtained by transformation into the global coordinates using the estimated parameters

6.2 Calibration of distributed cameras

Figure 10 shows reference path followed by mobile robots and camera arrangement. In this experiment, four CCD cameras are calibrated and two mobile robots with different height followed the same "∞" shaped path defined as

$$
\begin{aligned}
x &= \alpha_x \sin(\beta t / 2) \\
y &= \alpha_y \sin(\beta t)
\end{aligned}
\tag{14}
$$

where α_x, α_y, and β are constants, and t is a time step. Note that we can use an arbitrary path for calibration because we utilize only position information of the color markers. The observable area of each camera on the ground plane is about 4 meters × 4 meters. The captured image size is 320 pixels × 240 pixels.

In order to evaluate the accuracy of the proposed method, we made a comparison between the automated calibration and manual calibration. If the height of a place is known, the three
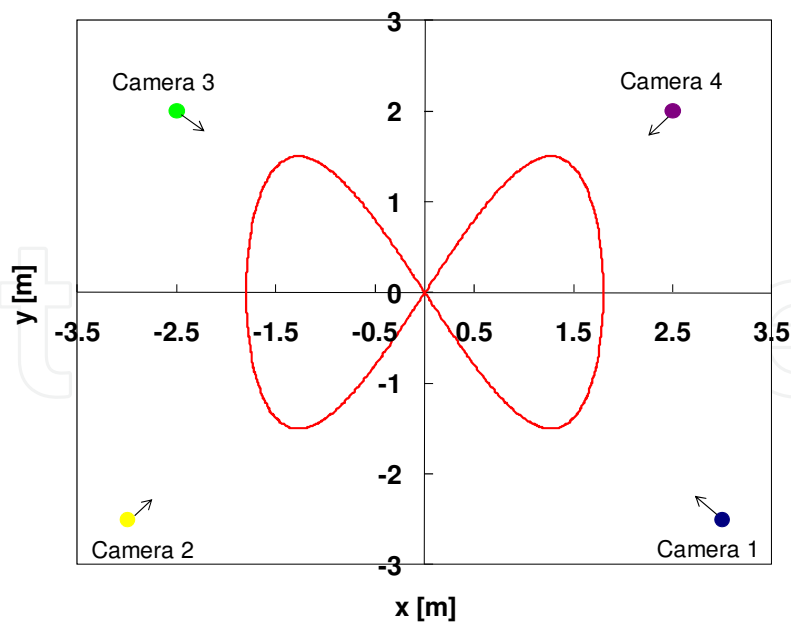
Fig. 10. Reference path followed by mobile robots and camera arrangement

dimensional position is reconstructed from one camera image. Therefore, we selected sample points shown in Fig. 11 from the image, and the corresponding positions on the ground plane (z=0) are reconstructed. The reference positions of sampled points are obtained from the ultrasonic 3D positioning system.

Table 2 shows the comparison of mean and maximum errors, which are the average and maximum Euclidean distance between the reference positions and the reconstructed positions of the nine sampled points, respectively. Although the difference of the average error is less than 8 millimeters, the manual calibration is more precise than the automated calibration in most cases. Especially, the maximum error is relatively large in the case of the automated calibration. This is mainly due to the fact that the obtained positions of the markers are not widely distributed on the image plane. This means that the path of the mobile robot is important for the calibration. In iSpace, this problem would be solved by mutual cooperation of DINDs and mobile agents - DINDs should ask mobile agents to move to the area where the corresponding points are not acquired enough.
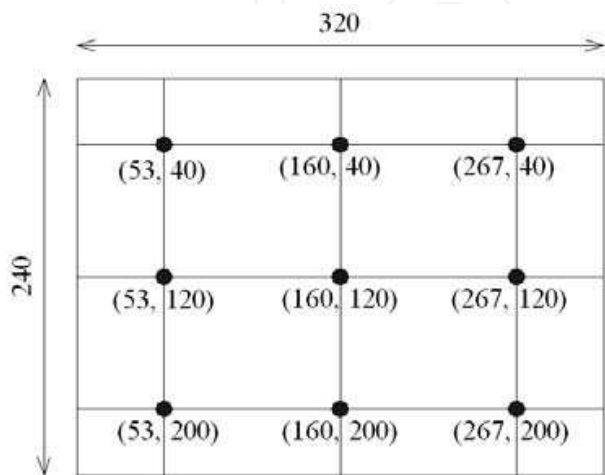

Fig. 11. Sampled points for evaluation of the camera calibration. The unit is in pixels.

Camera ID	Automated / Manual	
	Mean error [mm]	Maximum error [mm]
1	67.5 / 40.2	128.4 / 72.8
2	81.4 / 29.0	140.8 /54.7
3	54.6 / 64.6	116.4/ 91.3
4	32.6 /72.5	73.2 / 116.5
Average	59.0 / 51.6	114.7 / 83.8

Table 2. Comparison of mean and maximum error between automated and manual calibration of distributed cameras

7. Conclusion

We described an automated calibration method for distributed sensors in Intelligent Space (iSpace) by using mobile robots. The proposed method utilizes the positions of the robots in the world coordinate system and their corresponding points in the local coordinate system. The mobile robot localization and moving object tracking functions of iSpace are extended and calibration of distributed laser range finders and vision sensors is realized. In our work we used the ultrasound positioning system to localize the mobile robot. In a real environment this type of global positioning system is not always available, but it can still be possible to estimate the robot's position by using other already calibrated sensors or implementing a self localization method based on a preexisting map.

Performance of the proposed method was demonstrated experimentally. The experimental result shows that the method can provide enough accuracy for the various applications in iSpace such as mobile robot localization, human tracking, iSpace-human interface (Niituma et al., 2007) and so on.

For future work, since the proposed calibration method is affected by the error of the object tracking, we will develop a more accurate tracking algorithm. In addition, as mentioned in section 5.2, optimization of paths of mobile robots for calibration is another research direction. We will also consider utilization of the inter-sensor information for accuracy improvement and computational stability.

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Object Tracking

Edited by Dr. Hanna Goszczynska

Object tracking consists in estimation of trajectory of moving objects in the sequence of images. Automation of the computer object tracking is a difficult task. Dynamics of multiple parameters changes representing features and motion of the objects, and temporary partial or full occlusion of the tracked objects have to be considered. This monograph presents the development of object tracking algorithms, methods and systems. Both, state of the art of object tracking methods and also the new trends in research are described in this book. Fourteen chapters are split into two sections. Section 1 presents new theoretical ideas whereas Section 2 presents real-life applications. Despite the variety of topics contained in this monograph it constitutes a consisted knowledge in the field of computer object tracking. The intention of editor was to follow up the very quick progress in the developing of methods as well as extension of the application.

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