The Seventeenth International Symposium on Artificial Life and Robotics 2012 (AROB 17th '12),
B-Con Plaza, Beppu, Oita, Japan, January 19-21, 2012

A Cooperative Self-localization Method Based on Group Robot Information Sharing

Yuichi Kitazumi, Noriyuki Shinpuku and Kazuo Ishii

Kyushu Institute of Technology, Fukuoka 808-0196, Japan
(Tel: 81-93-695-6012, Fax: 81-93-695-6102)

kitazumi-yuichi@edu.brain.kyutech.ac.jp

Abstract: In the RoboCup MSL (Middle Size League), each robot should be autonomous and have fundamental abilities like obstacle avoidance, path planning, and cooperative behavior. Self-localization is one of the most basic and important functions for mobile robots, especially, multirobot system with cooperative behavior. We aim at improvement of self-localization accuracy of each robot of multirobot system by information sharing. To enhance the robot position accuracy, the soccer ball is used as the common landmark that just one exists in the playing field. In general, measured data, such as distances and angles to the white lines on the field, the ball, have measurement errors in the actual environment, so that we assume that the existence possibility of landmark position follows the Gaussian distribution. In our multirobot system, all robots share the group robot information such as estimated self-location and likelihood, distance and angle to the ball, role (defender, forward) via wireless LAN. Each robot evaluates the position likelihood of the landmark based on the landmark's existence probability. Then each robot corrects its position using fed-back the landmark position. In order to evaluate the efficiency of the proposed method in the real environment, the estimated self-location has been evaluated through experiments using the soccer robots "Musashi".

Keywords: *Multirobot System, Self-Localization, Information Sharing, RoboCup Middle Size League*

1 INTRODUCTION

For autonomous mobile robots, self-localization is one of the most fundamental and important information. Especially, when a multirobot system performs cooperative actions in real-time and actual environment, the importance of self-location increases. In the RoboCup Middle Size League (RoboCup MSL), the self-localization information of each robot is also important information for achieving the cooperative behavior [1][2].

In this research, the RoboCup MSL is selected as the target research platform for development and evaluation of multirobot system and cooperative behaviors, where maximum five robots from a team play soccer game and the collaborations with teammate robots such as pass and role change are inevitable to keep the rules. In the RoboCup MSL, active sensors like laser scanner are also allowed to obtain the surrounding environment, however, the playing field is the flat and simple symmetric environment with few landmark objects and often occupied by many mobile robots, therefore our robots obtain the environmental information mainly from an omni-vision sensor. In the beginning period of MSL, many variations of robots exist and many kinds of sensors are mounted, recently almost robots have an omni-vision system and an omni-directional mobile mechanism to be a holonomic system for easy motion planning [2-5].

Most of MSL robots estimate self-locations and the ball position from images of omni-vision systems using the white lines' position on the field and colored object position [6-8]. In our multirobot system, the distances to white lines are compared with the field model using particle filter and the self-location of each robot is estimated [8-10]. The absolute ball position is obtained by adding the robot self-location and the relative position of the ball from the robot.

We propose a cooperative self-localizing method which use the ball on the soccer field as the common landmark for all teammate robots, and self-locations are corrected by using the estimated absolute ball position by all robots. The proposed system represents the ball position by the existence probability functions for all robots depending on the distance, where the function show high value for the ball-closed robot and low for the robot far from the ball. By combining the probability functions, the ball existence probability map is generated and the proper ball position is estimated. Then, the robot positions and directions are also modified using the estimated ball position.

In experiments, the efficiency of the proposed method with group robot information sharing was evaluated using multirobot system RoboCup MSL by comparing the ball position and robots positions information sharing in real environment, and the experimental results show good improvement of self-locations of Musashi robots.

2 SINGLE ROBOT LOCALIZATION

In the proposed method, each robot estimates its position and direction by the Monte Carlo Localization (MCL) based on the geomagnetic data and the relative distance between the robot and white field lines [6-12]. The origin of the field map is the center of the field and the field is modeled in Cartesian coordinate taking x axis to the own goal direction.

The robot's state at time step t is represented by $\boldsymbol{x}_t = [r^x_t, r^y_t, {}^a\theta_t]^T$ which consists of its position (r^x_t, r^y_t) and heading ${}^a\theta_t$. The posterior probability $p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1})$ is calculated from $\boldsymbol{x}_t$ and time series of observed data $\boldsymbol{y}$. Here, $\boldsymbol{y}_t$ at time step t includes 60 relative distances to the closest white line every 6 degrees. In the MCL method, the probability distribution is represented by a set of N particles. In our application, each particle has $\boldsymbol{x}_t$ and $\boldsymbol{y}_t$ and the conditional probability $p(\boldsymbol{x}_t| \boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1})$ is specified by the previous state $\boldsymbol{x}_{t-1}$ and control input $\boldsymbol{u}_{t-1}$. Here, we use odometory data as $\boldsymbol{u}_{t-1}$. In order to apply MSL to self-localizing problem, we assume that the self-location probability follows the Markov decision process, and the posterior probability of current robot state is obtained by the following equation.

$$p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1}) = \int p(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}) \cdot p(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{1:t-1}) d\boldsymbol{x}_{t-1} \tag{1}$$

Next, as shown in eq.(2), $p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t})$ is updated based on the Bays theorem using likelihood $p(\boldsymbol{y}_t|\boldsymbol{x}_t)$ which is represented as the difference between line distances in each particle and observed data.

$$p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t}) = \frac{p(\boldsymbol{y}_t|\boldsymbol{x}_t) \cdot p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1})}{p(\boldsymbol{y}_t|\boldsymbol{y}_{1:t-1})} \tag{2}$$

The robot orientation is estimated from $\boldsymbol{x}_t$, however, the RoboCup MSL environment consists of symmetric and simple surfaces and always two candidate positions exist. That is, MCL has the possibility to select a wrong robot position in the MSL soccer field, called "Kidnapped Problem [13]". To help the problem, the geomagnetic sensor is utilized to have the robot direction. The predicted robot position is calculated by weighted average based on $\boldsymbol{x}_t$ and $p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t})$ as a weight. The self-localization process calculates the estimation iteratively. When the likelihood of estimated position from MCL is lower than a certain threshold (low reliability), the position from dead-reckoning method is adopted.

3 COOPERATIVE SELF LOCALIZATION

In our system, the self-localization is detected based on the visual information and wheel encoder data. Therefore the accuracy of self-localization depends on lighting condition, occlusions by opponent robots, and wheel slipping. In this paper, we consider the feature of multirobot system in RoboCup MSL, and propose a cooperative self-localization method based on information sharing among multirobots. The proposed method is realized by following steps.

Step 1. All robots find the ball and set as the common landmark.

Step 2. All robots share the ball position and self-position via wireless LAN.

Step 3. All robots estimate the proper ball position based on the shared information

Step 4. Using the estimated landmark (ball) position, each robot updates its position.

In this paper, the proper ball estimation of Step 3 is described "Landmark Estimation", and we call the estimated ball position by multi robots "the proper ball position" in followings. Self-position updating of Step 4 is described "Cooperative Self-Localization."

3.1 Landmark Estimation

In RoboCup MSL, many robots has omni-directional camera as an external sensor [5-8]. In this study, we assumed that the robot is equipped the omni-directional sensor and each object position is calculated using the own position and relative distances and angles between the robot and objects.

In general, the localization accuracy of object by the omni-directional camera depends on the distance from camera. In this process, each robot calculates the ball existence probability p^i_d by assuming the Gaussian distribution shown in eq.3. The variables p^x and p^y indicate the x and y coordinate of an arbitrary point on the soccer field, $\overline{m^i_x}$ and $\overline{m^i_y}$ do the x and y coordinate of the observed ball position from i-th robot ($\boldsymbol{m}^i=[m^i_x, m^i_y]^T$). Here, $\overline{m^i_x}$ and $\overline{m^i_y}$ are calculated as weighted average during n steps as shown in eq.4; we used the time-depending weight w_t. The parameters σ^i_d is the weighted variance parameters during n steps as shown in eq.5; $\overline{d^i}$ is the weighted average of the relative distance between the i-th robot and the ball from eq.6.

$$p^i_d(p^x, p^y) = \prod_{k=x,y} \frac{1}{\sqrt{2\pi\sigma^i_d}} \exp\left(-\frac{\left(p^k - \overline{m}^i_k\right)^2}{2\sigma^i_d} \right) \tag{3}$$

$$\overline{m}^i_{x,y} = \sum_{t=1}^{n} m^i_{x,y}(t) \cdot w_t \Bigg/ \sum_{t=1}^{n} w_t \tag{4}$$

$$\sigma^i_d = \sum_{t=1}^{n} \left(d^i(t) - \overline{d^i} \right)^2 \cdot w_t \Bigg/ \sum_{t=1}^{n} w_t \tag{5}$$

$$\overline{d^i} = \sum_{t=1}^{n} d^i(t) \cdot w_t \Big/ \sum_{t=1}^{n} w_t \tag{6}$$

The robot direction is estimated based on the MCL and heading sensor data, however the heading sensor data includes noise from magnetic distortion, so that the existence probability of the ball position p^i_s regarding magnetic compass is set to the Gaussian distribution in eq.7. As shown in Fig. 1, the parameter θ^i shows the angle between two lines; one line is from the *i*-th robot to the ball, and the other line is from the *i*-th robot to arbitrary point. The parameter r^i is the distance from the *i*-th robot to the arbitrary point, and l^i is the length of the arc; the center of the arc is the *i*-th robot position.

The parameter V^i is the weighted variance parameter regarding to the relative ball angle $\overline{\theta^i_{rel}}$ in robot coordinate during n steps as follows in eq.8. $\overline{\theta^i_{rel}}$ is calculated as weighted average during n steps as shown in eq.9. In the eq.10, we define that the variance for p^i_s is sum of the variance of heading sensor θ_{th} and V^i which regarding time. The ball existence probability is distributed along the circular arc, and the probability density takes the maximum value on the straight line L from the robot to the ball.

$$p^i_s\left(l^i\right) = \exp\left(-\frac{{l^i}^2}{2{\sigma^i_s}^2}\right) \tag{7}$$

$$V^i = \sum_{t=1}^{n}\left(\theta^i_{rel}(t) - \overline{\theta^i_{rel}}\right)^2 \cdot w_t \Big/ \sum_{t=1}^{n} w_t \tag{8}$$

$$\overline{\theta^i_{rel}} = \sum_{t=1}^{n} \theta^i_{rel}(t) \cdot w_t \Big/ \sum_{t=1}^{n} w_t \tag{9}$$

$$\sigma^i_s = r^i \cdot \sin\left(\theta_{th} + V^i\right) \tag{10}$$

In the proposed system, the conclusive ball existence probability p^i_{all} is calculated as the product of p^i_d and p^i_s in eq.11. Here, M is the number of robot in our team. Finally, we assume that the proper ball position p^i_{all} is the highest on the soccer field.

$$p^i_{all}\left(p^x, p^y\right) = \frac{1}{2M}\sum_{i=1}^{M}\left\{p^i_d\left(p^x, p^y\right) + p^i_s\left(l^i\right)\right\} \tag{11}$$

3.2 Cooperative Self-Localization

When the robot position has error, the observed ball position will be estimated far from the true ball position. It is desirable that the estimated robot position is adjusted near the true robot position by using the landmark, the ball position, so as to fit the observed ball position to the proper ball position. In the proposed system, we introduced an updating rule for ball position as shown in eq.12. α^i_d means the coefficient for updating the ball position based on the ball existence probability as following eq.13. γ^i_d is dumping factor which follow the feature of omni-directional camera as shown in eq.14. $d_{\min}$ means minimum relative distance between the robot and ball, and we set 0.4 as a $d_{\min}$ in this experiment.

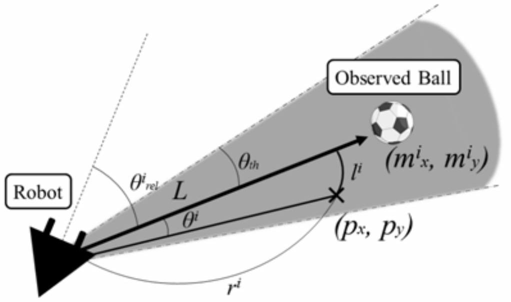
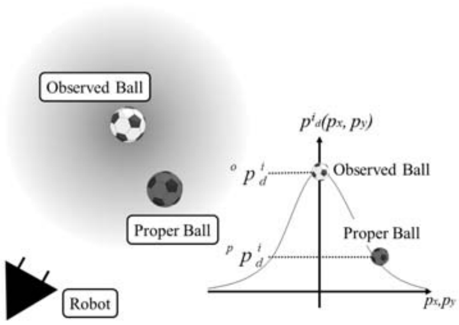


Fig. 1. Definition of existence probability p^i_s



(a) (b)

Fig. 2. Updating coefficient by parallel translation based on $^o p^i_d$ and $^p p^i_d$.

$$\Delta \boldsymbol{m}^i = \alpha^i_d \cdot \gamma^i_d \cdot (\boldsymbol{m}^i_p - \boldsymbol{m}^i_o) \tag{12}$$

$$\alpha^i_d = \frac{^o p^i_d - {^p p^i_d}}{^o p^i_d} \tag{13}$$

$$\gamma^i_d = \exp\left(d_{\min} - d^i(t)\right) \tag{14}$$

The robot position is also revised by parallel translation based on p^i_d and rotational translation based on p^i_s. $\boldsymbol{R(\theta)} \in \boldsymbol{R}^{3x3}$ is rotational matrix, and β^i_d means the coefficient for updating the robot angle based on p^i_s. θ_{pro} means the direction of the proper ball position in the robot coordinate. $^o p^i_s$ and $^p p^i_s$ are the observed and the proper ball position reliability regarding the ball angle.

$$\boldsymbol{x}_{t+1} = \boldsymbol{x}_t \cdot \boldsymbol{R}(\Delta\theta^i) + \left[\Delta \boldsymbol{m}^{i^T}, \Delta\theta^i\right]^T \tag{15}$$

$$\Delta\theta^i = \beta^i_d \cdot \left(1 - \gamma^i_d\right) \cdot \left(\theta_{pro} - \theta^i_{rel}\right) \tag{16}$$

$$\beta^i_s = \frac{^o p^i_s - {^p p^i_s}}{^o p^i_s} \tag{17}$$

Considering the parallel translation updating, let us consider the situation as shown in Fig. 2. Figure 2-(a) shows the observed ball and the proper ball, and the robot calculates the ball position reliability to take high value around observed ball position. ${}^{o}p^{i}_{d}$ and ${}^{p}p^{i}_{d}$ in Fig. 2-(b) are the probabilities of the observed and the proper ball position. Equation 17 is derived in the same way with the position updating. Finally, the robot state is updated by eq.15.

4 EXPERIMENTAL RESULTS

We evaluated the performance of the proposed system used soccer robot "Musashi [14, 15]" as shown in Fig.3 in real environment. In the experiment, five robots are set in the fixed positions as shown in Fig. 4. The ball moves from A(0.00, 0.00) to B(8.50, 0.00) at a speed of 3.0[m/s]. The color calibration was set by human operator, and the lighting condition was constant during experiment. In one experiment, 80 data of self-localization and the absolute ball position were recorded during the approximately 3.0[sec]. Figure 4 shows the position of each robot and the ball on the soccer field. The positions are goalkeeper:(9.00, 0.00), field-player1:(6.00, 3.00), field-player2:(3.00, 3.00), field-player3: (3.00, -3.00) and field-player4: (6.00, -3.00). The direction of the each robot was taken to the opponent goal. In consideration of the time delay in communication between robots, the position information of goalkeeper and the provided position information from field-players to goalkeeper were used for the experiment. Table 1 shows absolute errors of the proper ball position and observed ball position. Table 2 shows absolute robot state errors of self-localization by the single robot (MCL only) and multi robot (Cooperative Self-Localization).

In evaluation of the ball position, we focused on the y axis error e_{bd} of the ball and evaluated by eq.18. Here, N means data amount of self-localization and the absolute ball position, and m^{tr}_{y} and ${}^{n}m^{i}_{y}$ is proper y position of the ball and y position of observed or estimated ball.

$$e_{bd} = \frac{1}{N}\sum_{n=1}^{N}\sqrt{\left(m_y^{tr} - {}^{n}m_y^{i}\right)^2} \qquad (18)$$

The absolute robot state errors e_{rp}, e_{ra} are evaluated by eq.19 and eq.20. r^{ty}_{x}, r^{ty}_{y} and θ^{r} is correct robot state, respectively. And also, ${}^{n}r^{i}_{x}$, ${}^{n}r^{i}_{y}$ and ${}^{n}{}_{a}\theta^{i}$ means robot state at time-step n.

$$e_{rp} = \frac{1}{N}\sum_{n=1}^{N}\sqrt{\left(r_x^{tr} - {}^{n}r_x^{i}\right)^2 + \left(r_y^{tr} - {}^{n}r_y^{i}\right)^2} \qquad (19)$$

Dimensions	Triangle 520[mm], Height 800[mm]
Weight	19.0[kg]
Motor	Maxon DC Motor 70[W] x 3
Motor Driver	Faulhaber MCDC 2805 x 3
Wheel	Omni wheel x 3
Battery	Li-Polymer Battery 25.9[V] 2000[mAh]
Sensors	Omni Camera, Digital Compass

Fig.3. Overview and Specification of "Musashi"

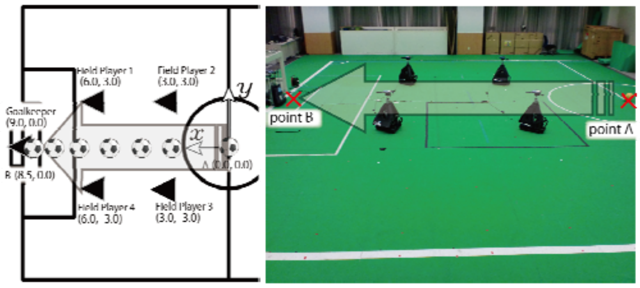


Fig. 4. The experiment condition in dynamic environment

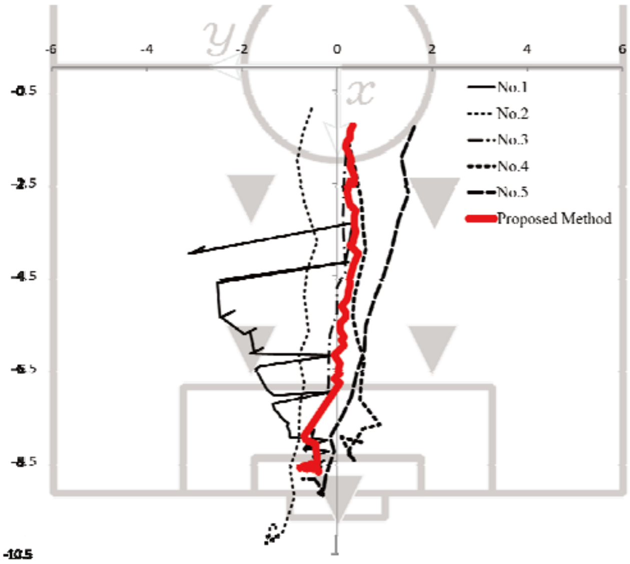


Fig. 5. Orbits of observed ball and proper ball

Table 1. The result of landmark estimation

	No.1 [m]	No.2 [m]	No.3 [m]	No.4 [m]	No.5 [m]	Proposed Method [m]
e_{bd}	1.09	0.91	0.33	0.46	0.61	0.39
SD	0.82	0.31	0.23	0.16	0.44	0.20

Table 2. The result of cooperative self-localization

	Single Localization		Multi Localization	
Position[m]	e_{rp}	SD	e_{rp}	SD
	0.36	0.09	0.34	0.09
Angle[deg]	e_{ra}	SD	e_{ra}	SD
	25.05	9.62	14.54	12.04

$$e_{ra} = \frac{1}{N}\sum_{n=1}^{N}\sqrt{\left(\theta^{tr} - {}_{a}^{n}\theta^{i}\right)^{2}} \qquad (20)$$

In table 1, the absolute observed ball position error of goalkeeper included 1.09[m] in average, and also standard variation (*SD*) was 0.82[m]. As shown in Fig.5, the observed ball position error was reduced when the ball moved until near the robot. The absolute ball position error of landmark estimation showed 0.39[m] in average and *SD* was 0.20[m]. This result indicates the landmark estimation could reduce the absolute ball position error than the absolute observed ball position error of goalkeeper. Table 2 shows the absolute robot state error of cooperative self-localization was smaller than the single robot localization. The absolute robot position error of single robot localization was 0.36[m] in average and *SD* was 0.09[m], and also the aboslute angle error was 25.05[deg] in average and *SD* was 9.62[deg]. In the results of cooperative self-localization, the absolute robot position error was 0.34[m] in average and *SD* was 0.09[m], the absolute angle error was 14.54[deg] in average and *SD* was 12.04[deg]. This result indicates the robot state was guided to the proper robot state, however the standard variation of the observed information affects the result of cooperative self-localization.

5 CONCLUSION

We proposed a cooperative self-localization method based on group robot information sharing using the landmark position and implemented the proposed method to a multirobot system "RoboCup MSL robots". The performance of the poposed method has been evaluated using five autonomous mobile robots. This experimental results show that the ball estimation based on the information sharing increases the reliability of ball existence. In RoboCup MSL environment, it is mentioned that the reliable ball position can be shared with the robot which cannot observe a ball due to increasing the reliability of the ball position. In addition, cooperative self-localization can adjust the robot positions to the proper position.

As a future work, we apply the proposed method to realize the cooperative behaviors such pass, drible, and shoot.

REFERENCES

[1] H. Matsubara, et al., "History of RoboCup and Prospects of RoboCup-2002", RSJ, Vol.20, No.1, pp.2-6

[2] S. Monteiro, F. Ribeiro,Paulo Garrido,"Problems and Solutions in Middle Size Robot Soccer – A Review", Robotica'2001 - Festival Nacional de Robótica, pp.25-28, April 2001, Guimarães, Portugal, 2001.

[3] D. J. H. Bruijnen, et al., "Tech United Eindhoven: Team Description 2010", RoboCup 2010 in Singapore

[4] M. Gholipuor, et al., "MRL Middle Size Team: 2010 Team Description Paper", RoboCup 2010 in Singapore

[5] A. J. R.Neves, J. L. Azevedo, et al. "CAMBADA'2010: Team Description Paper", RoboCup 2010 in Singapore

[6] Martin Lauer, Sascha Lange and Martin Riedmiller, "Calculating the perfect match: An efficient and accurate approach for robot self-localization", In A. Bredenfield, RoboCup 2005: Robot Soccer World Cup IX, LNCS, Springer, 2005.

[7] A.Merke, S. Welker, and M. Riedmiller, "Line Based robot localization under natural light condition", In ECAI 2004, Workshop on Agents in Dynamic and Real-Time Environments, Valencia, Spain, 2004

[8] Amir A. F. Nassiraei, Y. Kitazumi, "Hibikino-Musashi Team Description Paper", RoboCup 2010 in Singapore

[9] Y. Sato, et al., "A Study of Line Based Localization for RoboCup Middle Size League", Proc. of the 2008 JSME Conference on Robotics and Mechatronics, 2P1-J14, Nagano, Japan, 2008, in Japanese

[10] N. Shinpuku, I. Godler, "Robot Self-Localization Using Particle Filter in RoboCup Middle Size League", Proc. of the 2010 JSME Conference on Robotics and Mechatronics, 1P1-F26, Asahikawa, Japan, 2010, in Japanese,

[11] S. Thrun, et al., "Robust Monte Carlo Localization for Mobile Robot", Artificial Intelligence Journal, Vol.128, No.1-2, pp.99-141

[12] F. Dellaert, et al., "Monte Carlo Localization for Mobile Robots", Proc. of 1999 IEEE International Conference on Robotics and Automation, Vol.2, pp.1322-1328, Detroit, 1999

[13] R. Ueda, et al., "Recovery Methods for Fatal Estimation Errors on Monte Carlo Localization", Journal of the Robotics Society of Japan, Vol.23, No.4, pp.466-473, 2005, in Japanese

[14] A. A. F. Nassiraei, et al., "Concept of Mechatronics Modular Design for an Autonomous Mobile Soccer Robot", ICRA2007, pp.178-183, Jacksonville

[15]Y. Takemura, et al., "Auto Color Calibration Algorithm Using Neural Networks and its application to RoboCup Robot Vision", International Journal of Artificial Intelligence, Vol.7, pp.368-383