Robustness Verification Against Noise of Self-localization Method Using Omni-directional Camera for Soccer Robot

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Abstract

The main focus of the RoboCup competitions is the game of football/soccer, where the research goals concern cooperative multi-robot and multi-agent systems in dynamic adversarial environments[1]. In the field of RoboCup, self-localization technique is important to estimate own position including goal and other robot positions and to decide strategy. This paper presents a self-localization technique using an omni-directional camera for an autonomous soccer robot. We propose the self-localization method with white line information of soccer field, and recognize the robot position by optimizing the fitness function using Genetic Algorithm. Moreover, we also verify the robustness of the proposed method against noise through experiments.

Keywords: Robustness Against Noise, Self-Localization, RoboCup Middle Size League, Soccer Robot, Genetic Algorithm

1. Introduction

In the field of RoboCup, self-localization technique is important to estimate own position including goal and other robot positions and to decide strategy. Basically, we estimate the self-position with the image information, the environment information and the field information. In this paper, we describe a real-time self-localization method that applies a genetic algorithm (GA) for the RoboCup middle size league, and verify the robustness detection of this method.

2. Hardware of vision system

About the omni-directional vision system of our robot is consisted of the camera (FLIR, Flea3[2]), a varifocal lens (Vstone) and a hyperboloidal mirror (Vstone). We developed vision system shown in Fig. 1 for RoboCup MSL robot by combining with above elements[3]. The image captured by this vision system is shown in Fig.

Fig. 1. Hardware of vision system

2(a), and the image size and frame rate are 512 × 512 [pixels] and 30 [fps] respectively.

3. Self-localization

We use a white line of MSL field for self-localization. We have proposed the self-localization method, which generates the searching space based on a model based matching using white line information[4]. And this method recognizes the robot position by optimizing the fitness function, which has the maximum value at correct robot position. Moreover, this proposed self-localization method employs Genetic Algorithm (GA)[5] for optimization of the fitness function.

3.1. *Searching model*

Figure 2 shows the process of making the searching model of the proposed method. At first, we need the detection image of the white line for making the searching model. We obtain the white detection image by employing the converting method of color space from RGB to HSV and to YUV like Fig. 2b. Then we generate the field information by orthogonalizing the white line information like Fig. 2c. Moreover, we determine the searching model by thinning down the field information based on white line like Fig. 3d. Therefore, we use thinned model as searching model for the self-localization.

3.2. *Model-based matching*

The proposed self-localization method generates the searching space by model based matching between geometric information of the white line in the MSL field and above-mentioned searching model. We use this method to calculate the evaluation function $F(\tilde{\phi})$, $\tilde{\phi} = [\tilde{x}, \tilde{y}, \tilde{\theta}]$. The fitness function $F(\tilde{\phi})$ obtains the maximum value when the position of the searching model corresponds to the correct position that robot exist in the MSL field. Then, the problem of detection of robot position is converted to the searching problem of $\tilde{\phi}$ such that $F(\tilde{\phi})$ is maximized. Due to the revolution symmetry of the white line of the MSL field, we may get two maximum value exist in the fitness function. Here, we select only one depending on an electric compass.

3.3. *Genetic Algorithm*

In the proposed self-localization method, we employ Genetic Algorithm (GA) for searching the maximum value of the fitness function $F(\tilde{\phi})$. A GA is an example of an artificial intelligence program and is well known as a parallel search and optimization process that mimics natural selection and evolution. In the proposed method, an elitist model of a GA that preserves the best individual in the population at every generation is utilized and

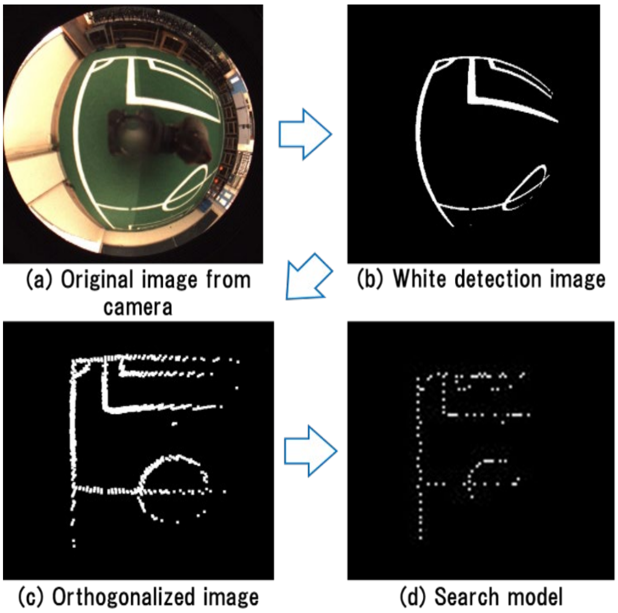
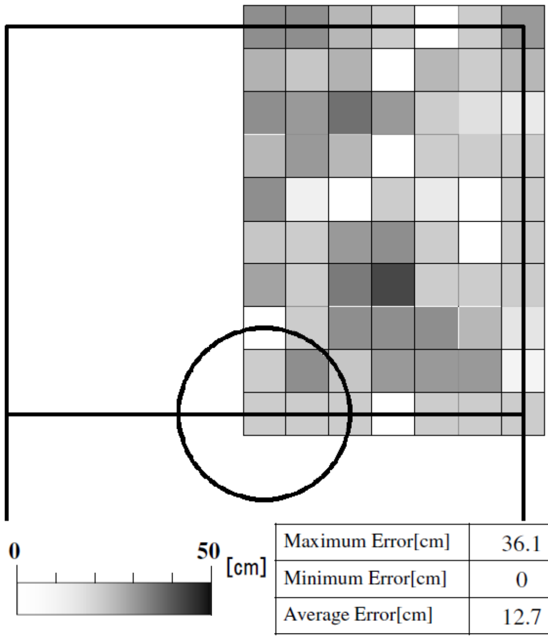


Fig. 2. Process of making search model



Maximum Error[cm]	36.1
Minimum Error[cm]	0
Average Error[cm]	12.7

Fig. 3. Error of the self-localization

genetic coding using gray code, roulette selection and one-point crossover are employed. And, the parameters of the GA process are determined by previous experiments.

3.4. *Verification experiment*

We performed the self-localization experiment to verify the effectiveness of the proposed method. Figure 3 shows the result of the verification experiment that checked the self-localization error between correct position and detected position at the quarter area of the MSL field at interval of one meter. In this figure, each box represents the error as the brightness of gray scale. Average error of this experiment was 12.7[cm], and the accuracy of the self-localization by the proposed method is enough to play soccer.

Fig.5. Experiment location

4. Robustness verification

The accuracy measured so far is the result of an ideal environment when there are no other robots on the soccer field. However, in a real game environment, up to ten robots may exist in the same soccer field. In addition to the robots, there are humans such as the referee and the line referee at the same time on the field. Then the robot may not be able to recognize correct own position, because these become an occlusions. Therefore, to verify the robustness of proposed method against various noise, we conducted experiments.

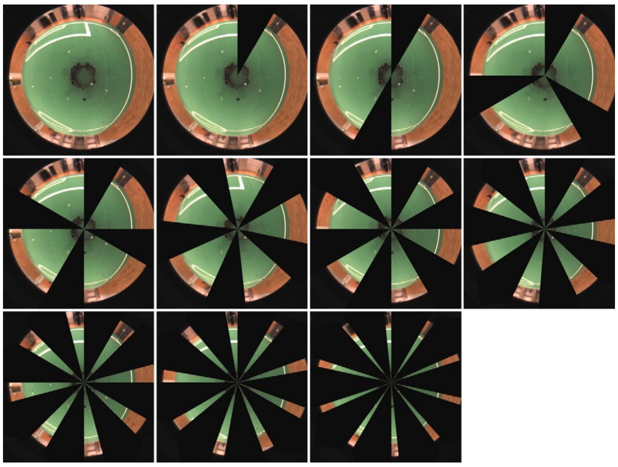


Fig.6. Noise at different amounts

4.1. *Experiment*

In a real environment, there will be a variety of noises appearing on the image, and we cannot perform qualitative experiments. Here we perform verification experiments by adding artificial noise.

We conducted the experiments at the seven locations in the MSL field indicated in Fig. 5. These seven locations are especially characteristics point in MSL field. Taking the center of the panoramic image as the center of the circle, we set the fan-shaped area with a center angle of 30 degrees as a noise like Fig. 6. By changing the position and number of the noise, we can simulate different noise conditions, and verify the results of self-localization.

Figure 6 shows the change in the number of noise at the position Fig. 5(d), and the change in angle is shown in Fig. 7. The image in the top left of Fig. 6 is original image without any noise. We verify the error of self-localization results measured at the angle and number of various noise at each coordinate location in the MSL field. And the results of each measurement position are

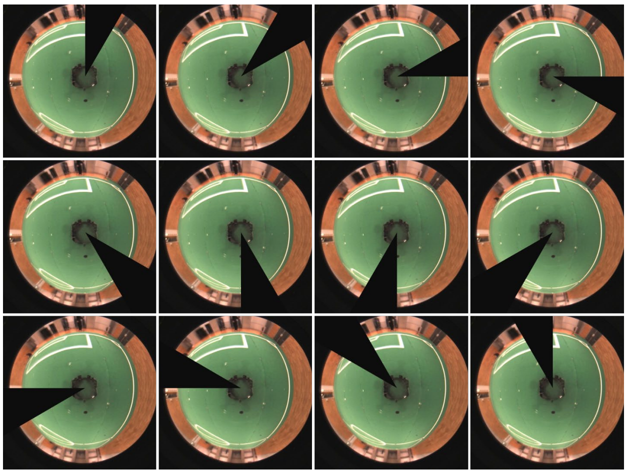


Fig.7. Noise at different angles

Table 1. Error comparison result

	Error[cm]	Noise num									
	Rate	1	2	3	4	5	6	7	8	9	10
Point	A	28.3	28.3	28.3	28.3	150.3	22.4	72.8	1510.0	28.3	131.5
		0.00%	0.00%	0.00%	0.00%	8.33%	0.00%	8.33%	66.67%	0.00%	16.67%
	B	14.1	14.1	14.1	14.1	31.6	14.1	41.2	22.4	648.5	1164.8
		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	50.00%	100.00%
	C	10.0	14.1	0.0	10.0	14.1	10.0	14.1	10.0	14.1	10.0
		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
	D	20.0	14.1	10.0	20.0	20.0	10.0	1310.3	429.5	676.8	1207.8
		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	8.33%	66.67%	75.00%	100.00%
	E	22.4	22.4	22.4	58.3	1650.5	22.4	22.4	31.6	31.6	31.6
		0.00%	0.00%	0.00%	33.33%	8.33%	0.00%	0.00%	0.00%	0.00%	0.00%
	F	30.0	30.0	41.2	14.1	20.0	40.0	20.0	40.0	41.2	370.1
		0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	66.67%
	G	10.0	10.0	40.0	120.0	40.0	10.0	820.1	900.1	890.1	900.1
		0.00%	0.00%	0.00%	33.33%	0.00%	0.00%	33.33%	66.67%	75.00%	66.67%

summarized in Table 1. For the position deviation caused by the noise of different angles, we take the average value combined with the deviation value caused by the amount of noise. The red grid in the table indicates that the error value of the self-localization exceeds the width of a robot (50cm). It means that the robot has lost its accurate position.

4.2. *Experiment results*

According to the results in Table 1, when the number of noises increases, the error of self-localization also increase. Overall, when the number of noises is greater than 7, it will cause large errors except for special locations. Here, the special locations is when there are more than two features in the image obtained by the robot (Location B and F) or when the robot is in the center circle (Location C). Location E and G also have errors when the amount of noise is not large. The reason may be that the robot is on the white line crossed vertically, and the 4 noises hide all the white line information. Overall, from the results in Table 1, when the number of noises is less than 3, the error of self- localization is very small. And when the number of noises increases to 4, the maximum error of self- localization is 120cm. In a real game environment, the probability of more than 4 noises existing at the same time is very small. Therefore, this method has robustness against noise enough to play soccer.

5. Conclusion

In this paper, we have proposed the self-localization method that generates the searching space based on a model based matching with white line information of RoboCup MSL soccer field, and which recognizes the robot position by optimizing the fitness function using Genetic Algorithm. Moreover, we have verified the effectiveness and accuracy of the proposed self-localization method using GA. Furthermore, we confirmed that the robustness against noise of the self-localization by the proposed method is enough to play soccer through experiments.

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