Improvement of Multiple Robots' Self-localization by Using Perspective Positional Information

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Abstract

This study [1] aimed to improve the precision of multiple robots' self-localization in the standard platform league of RoboCup, i.e. a robotic soccer competition. For improving the precision of the self-localization, we proposed a new technique that uses an external camera out of the field for assistance. Robots in the field use the unscented particle filter that estimates their position from some landmarks. When a robot equipped with the filter cannot recognize any landmarks exactly, particles spread and the precision of the self-localization decreases. Therefore, the overlooking camera out of the field observes each robot's position. When particles spread, the external camera estimates the foot position of the robot, and then the robot sprinkles particles on the neighborhood again. In this way, even if a robot cannot recognize landmarks exactly, assists of the external camera revise the position of particles and improve the precision.

1 Introduction

The RoboCup (Robot Soccer World Cup) project sets a goal that a fully autonomous robot team shall win against the most recent winning team of FIFA World Cup in soccer by 2050.

The RoboCup Soccer Standard Platform League (SPL) is a league that all teams compete with the same standard humanoid robot called NAO developed by Softbank Robotics[1]. The robot operates fully autonomously, that is with no external control, neither by humans nor by computers. In RoboCup Soccer SPL, the robot must process all the calculations on vision processing and decision making using low-end CPU (Intel Atom 1.6GHz). In addition, the robot must devote a lot of computation resource to percept a white goal and a mostly white ball in vision processing. Each team has five player robots and optionally has one coaching robot that can send instructions at a perspective view from outside the field. An example of the positional relationship between the field and the coaching robot is shown in Figure 1.

In RoboCup Soccer SPL, a self-localization mechanism that estimates player own position and orientation is required. We use the unscented particle filter (UPF)[3] which is currently a mainstream method[4] for self-localization. However, a robot cannot accurately grasp any landmarks, then particles do not converge, so the estimation error of self-localization becomes large.

In addition to the conventional method, by using the coaching robot as the observer, an area where a player is likely to exist is specified. We propose a method to promote convergence of particles by correcting the coordinates of scattering particles based on the information from the coaching robot. From this method, estimation error of the self-location is assumed to be suppressed when the player cannot accurately recognize landmarks.

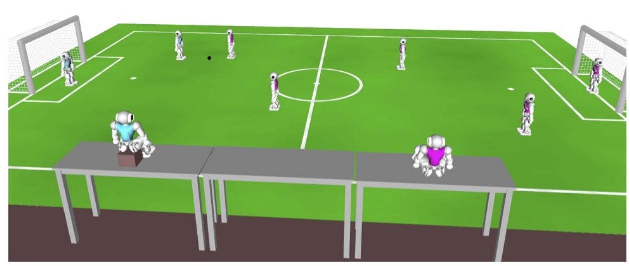

Figure 1: Coaching robots can observe the almost whole field[2]

2 Unscented Particle Filter (UPF)

The UPF is a combination of the unscented Kalman filter (UKF)[5] and a particle filter (PF)[6]. The difference between UPF and PF is that UPF is used the UKF for updating each particle.

The UPF estimates the position of the robot by using

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a finite number of particles assumed to be the robot. The first step is motion update step. In this step position of each particles is updated the by using robot motion information. The second one is measurement update step. The robot calculates the weight of each particles based on observation information. The third one is resampling step. It sprinkles the particles according to the weights.

3 Proposed method

When UPF cannot accurately grasp landmarks, particles may not converge. When such a situation occurs, the coaching robot behaves as an observer, assists to estimate the self-localization of the player from the outside, and encourages the convergence of the particles. The flow of the proposed method is shown in Figure 2.

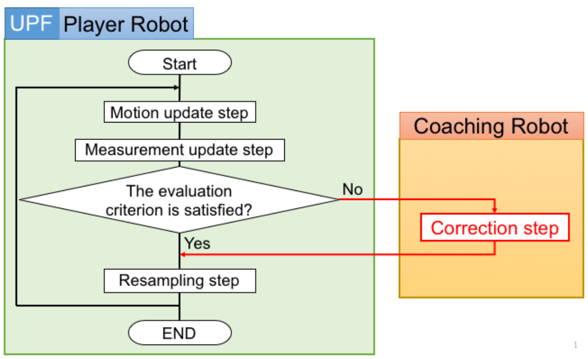

Figure 2: Outline of proposed method

3.1 True perspective image

At first, the coaching robot gets a perspective image as shown in Figure 3. Then it is transformed to a true perspective image by using homography transform[7] (see Figure 4). Since the homography transform requires more than four coordinates on an image, the coaching robot will select more than four points out of 17 candidates, i.e. four corners of the field, eight corners of the penalty areas, two penalty marks, two intersections of the center line and the side lines, and a point of the center mark. In Figure 3, we use eight points by indicating red circles.

Figure 3: Original image with known positions.

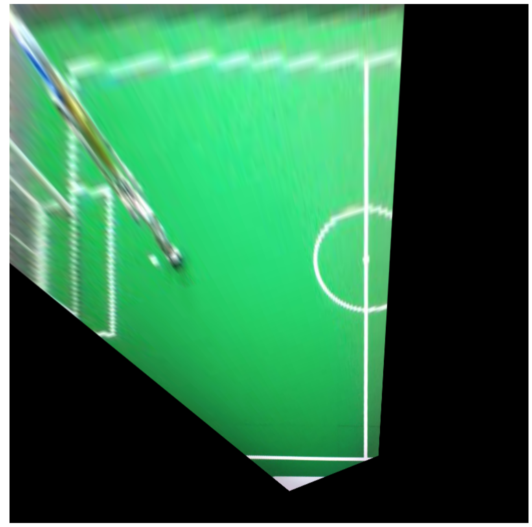

Figure 4: Homography transformation

3.2 Estimation of a player's position

We estimate straight lines with a high possibility that a robot exists. Only the jersey regions are extracted from the transformed image. Then, the regions are denoising by opening processing[8] (see Figure 5) and Increasing connectivity by closing processing[8]. After that, we extract regions of the own team's jersey, they are certain that the player robot will be on the line calculated by simple linear regression analysis (see Figure 6).

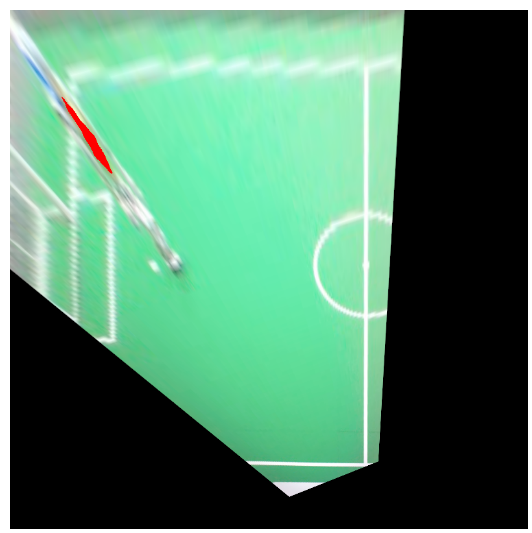

Figure 5: Extraction of uniform

3.3 Estimation of a player's foot position

We estimate the foot of the player robots and use it as the reference of the position at which particles are resampled. The foot position of the player robot is estimated as the bottom point of regions excluding the field on the line(Figure 6). We transform the color space of the perspective image into L*a*b* to detect the color of the green field. L* stands for lightness and a* and b* are chromaticness index equivalent to hue and sat-

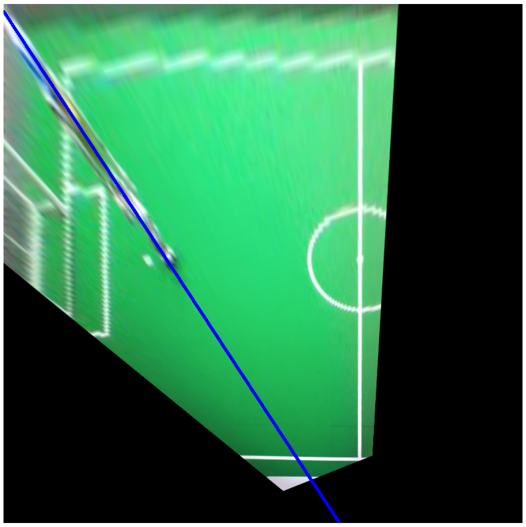

Figure 6: Straight line expressing rough robot position

uration. The color approaches red as the value of a* becomes high and green as it becomes low, and yellow as the value of b* becomes high and blue as it becomes low. We binarize the image of a* by Otsu's thresholding method[9]. By doing so, we extract regions other than the green color of the field. As applying the homography transform to the image, the true perspective image is shown in Figure 7. There is a possibility that the estimated position of the feet may be displaced by the line of the field in Figure 7. Therefore, the region of the moving object is extracted using the background difference and the position of the robot is specified. The region of the moving object obtained from the background subtraction is shown in Figure 8.

The region with the most continuous region of Figure 7 on the straight line is extracted. The lowest point of the region of Figure 8 included in this region is regarded as the foot. The estimated foot position is illustrated in Figure 9 as a red circle.

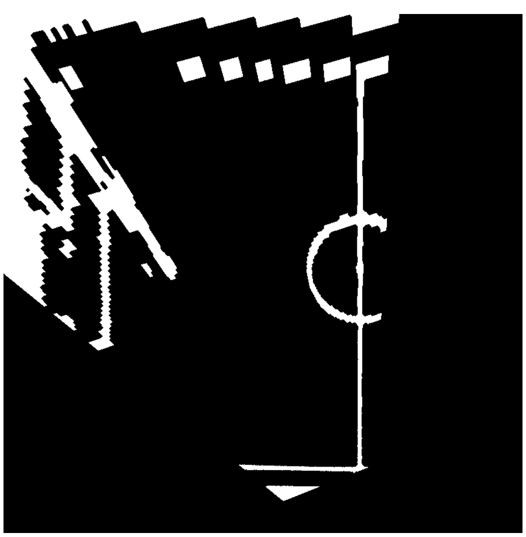

Figure 7: Image except green field region

Figure 8: Background subtraction

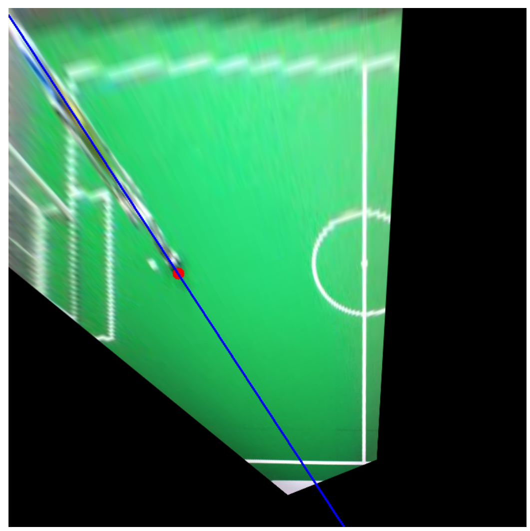

Figure 9: Estimated position of robot's foot

4 Experiment

We verify whether the player can be assisted self-localization of using images acquired by the coaching robot. Firstly, it is evaluated how the estimated foot position is closer to the true one by comparing the proposed and the conventional methods. Secondly, after correcting the position of the particle by the proposed method, it is verified whether it is close to the true position as compared with the conventional method.

The experiments were conducted and used two players under an LED uniform lighting environment with natural light. We use the OpenCV 3.1 library as a tool for image processing. The value of α in the normal distribution in Section 3.4 is empirically set to 8 in order to prevent particles from spreading. The number of particles is 12.

3.4 Determination of resampling position

Based on the estimated foot position, the locations where particles are scattered are determined. Taking into account the error of the estimated foot position, the positions of particles are determined according to the normal distribution as given by Eq. (1).

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{1}$$

where μ is the mean and σ^2 is the variance. In this paper, the value of μ is defined by the foot position x, and the value of σ is set to $1 / \alpha$. The particles are gathered into the foot estimated by increasing the value of α. Based on the above, the positions of particles are indicated by yellow circles in Figure 10.

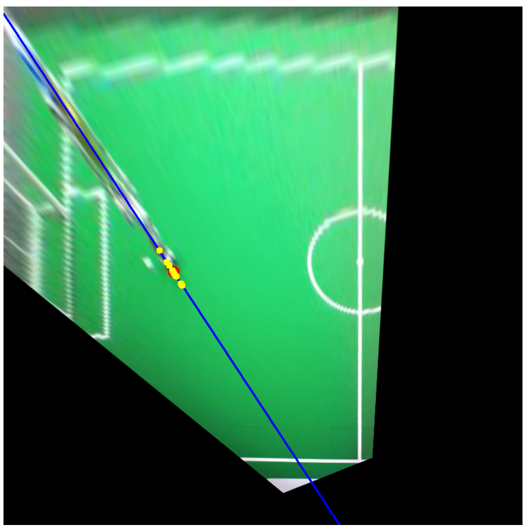

Figure 10: Resamped position of particles

4.1 Experiment 1: Verification of the accuracy of the estimated foot position

When distributing particles using the proposed method, the estimated position accuracy of the estimated foot position of Section 3.3 is important.Because the coordinates of particle resampled are highly based on the foot position. Therefore, we verify the accuracy of the estimated foot position using the proposed method by measuring the actual foot position. In addition, we compare the estimation error of the self-localization with the conventional method.

In this experiment, two conditions are set in order to see the change in error according to the distance between the coaching and the player robots. Therefore, we estimate the foot positions of two robots simultaneously. As shown in Figure 11, the robot is placed, the robot A is closer to the coaching robot, and the robot B is far one.

In the experiment, the robots follow a path as shown in Figure 11 where landmarks such as lines and goals are difficult to recognize and self-position estimation becomes difficult. We set the player robots in the red circles as the initial state and walk to the blue circles according to the red arrows. At that time, self-position estimation is performed using UPF. When both the robots reached the blue circle, the coaching robot estimates the foot position of the player robots. Experiments were carried out three times and the errors against the true position are averaged to compare the accuracy.

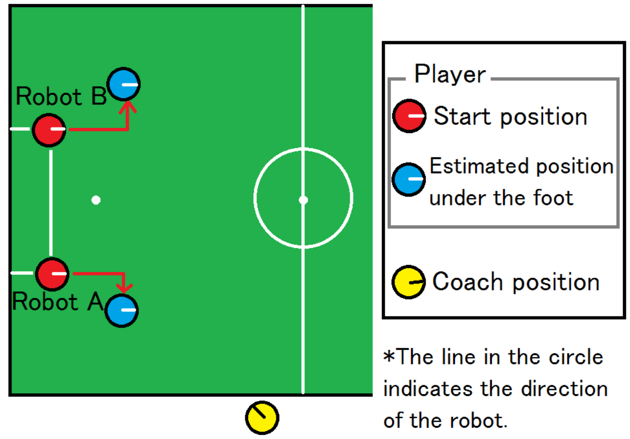

Figure 11: Routes in experiment 1

4.2 Result of Experiment 1

The experimental results in Experiment 1 are shown in Table 1. Improved rate in Table 1 is obtained from Eq. (2). In Eq. (2), R is the Improve rate, Ec is the error average of the conventional method, and Ep is the error average of the proposed method.

$$R = \frac{E_c - E_p}{E_c} * 100 \tag{2}$$

From Table 1, Both the robots A and B are more accurate than the conventional method, so it can be applied even in situations where there is a difference in observation distance between the coach robot and the player robot. In addition, the total improvement rate of the accuracy of the estimated position at the total of 6 times by the two robots A and B three times is 74%.Therefore, on the basis of the estimated foot position, resampling particles is expected to improve the accuracy. Moreover, we could confirm that it is possible to estimate not only one robot but also multiple robots.

Table 1: Average error of the estimated foot position (Experiment 1)

	Average error [mm]	
Method \Robot	Robot A	Robot B
Conventional method	630	450
Proposed method	199	80
(Improved rate [%])	(68)	(82)

4.3 Experiment 2: Verification of the accuracy of self-localization after resampling

After resampling the particles using the proposed method, the robot moves again and the self-position estimation accuracy at the last position is verified. We also compare the estimation error of the self-localization with the conventional method.

As seen in Section 4.1, the player robots moves by two kinds of routes as illustrated in Figure 12 . Experiments were carried out three times and the errors against the true position are averaged to compare the accuracy.

As in Experiment 1, robots walk to the blue circles in Figure 12, then correct the particle position only once using the proposed method at the position of the blue circles. After that, when it reaches the gray circle along the red solid arrow shown in Figure 12, it estimates its own position. We compare the accuracy of self-position estimation with the normal UPF and that with the proposed UPF that corrected particles only once using the proposed method.

When resampling is performed using the proposed method, the direction of the particles is determined according to the normal distribution based on the estimated direction. The normal distribution is given by Eq. (1). In self-localization, the direction is corrected by recognizing landmarks. Therefore, the value of μ is set to the previous estimated direction and the value of σ is empirically set to $\pi/8$.

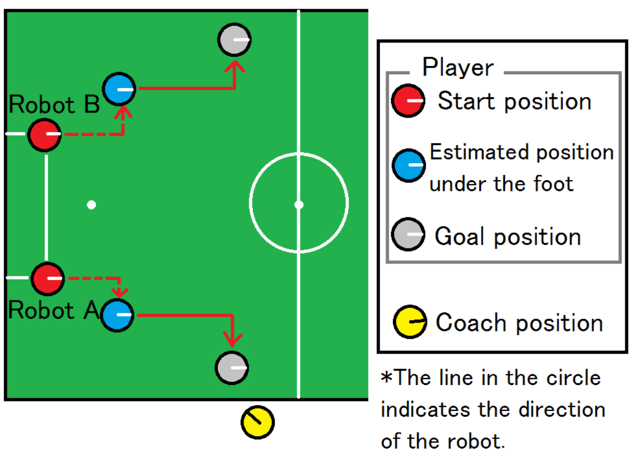

Figure 12: Routes in experiment 2

4.4 Result of Experiment 2

The results in Experiment 2 are shown in Table 2. Improved rate in Table 2 is obtained from Eq. (2).

From Table 2, both the robots A and B using the proposed method are more accurate than those using the conventional method., so it can be applied even in situations where there is a difference in observation distance between the coach robot and the player robot. In addition, the total improvement rate of the accuracy of the estimated position at the total of 6 times by the two robots A and B three times is 72%. Moreover, we could confirm that it is possible to estimate not only one robot but also multiple robots.

The coaching robot can not always estimate the feet of the player robot at all times. However, once using the proposed method from this experiment, it was confirmed that the estimation accuracy was improved after that. Therefore, under the situation where the player's foot can be estimated, it is expected that the estimation accuracy after that can be improved by using the proposed method.

Table 2: Average error of self-localization (Experiment 2)

	Average error [mm]	
Coach \Robot	Robot A	Robot B
without coach	987	606
with coach	169	274
(Improved rate [%])	(83)	(55)

5 Conclusion

In this paper, we proposed a method for improving the accuracy of the self-position estimation method, the UPF, in the RoboCup soccer standard platform league. In the proposed method, the position of the particle is corrected by using the observer (coach robot) assisted the subjects (player robots) who performs self-position estimation. As a result, by using the proposed method, the estimation accuracy of the self position is improved by 72% compared with the conventional method.

In addition, since improvement of estimation accuracy after that can be confirmed by correcting the position of the particle once using the proposed method, it is expected that estimation accuracy will improve only by using the proposed method when the coaching robot can estimate player's foot.

As future work, when there are two or more player robots as in a normal game, it is necessary for the player robot to discriminate from the position information of the player robot estimated by the coaching robot which information about ourselves.

Acknowledgements

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