Autonomous mobile soccer robot localization using particle filter through Omni-vision

N A Mardiyah[1,*], N Setyawan[1] and M N Achmadiyah[2]

[1]Department of Electrical Engineering, University of Muhammadiyah Malang, Malang, Indonesia
[2]Department of Electronics Engineering, State Polytechnic of Malang, Malang, Indonesia

*nuralif@umm.ac.id

Abstract. "Where am I?" is the primary question, which is the representation of localization, that the mobile soccer robot must be answered. Dead reckoning is the most popular method used in a wheeled mobile robot. However, the increasing position error is the main topic of the dead reckoning method. Furthermore, in this paper, the localization of a mobile soccer robot using a particle filter through Omnivision is proposed. The sensor model and motion model of particle filter are also discussed, where the sensor model is obtained from segmentation and feature extraction of the soccer field landmark. The experimental result showed that the proposed method estimated the robot position accurately with 15% error.

1. Introduction

"Where am I?" is a fundamental question which must be answered by an autonomous mobile robot before it moved. That question is also a representation of the positioning of an autonomous mobile robot or called localization. Localization is also a primary problem for autonomous mobile robot soccer. In mobile robot soccer, before it chose an action to move, the mobile robot position according to field coordinate, ball position, and the goal post must be well known. Ball positioning using hybrid Particle Swarm Optimization-Neural Network (PSO-NN) has been proposed in Setyawan et al. [1]. The goal post position using color-based segmentation and feature extraction has been introduced in Fitriana et al. and Setiawardhana et al. [2,3]. Furthermore, various methods have been proposed for localization of a wheeled mobile robot. The dead reckoning using some rotation sensors has been implemented in Kurniawan et al. and Bahtiyar et al. [4,5]. The dead reckoning method computes the translation movement of the robot by counting the pulse from wheel rotation sensors. The localization using dead reckoning is computation less. However, the accuracy is decreasing when some error happens, which can increase the error in every movement, i.e., wheel slip. It is not suitable for soccer robot cause there are some collision between robot can happen.

Visual localization is another option that can be implemented in a soccer robot. The visual localization using some visual information from the soccer field to compute the robot position, i.e., goalpost, line of the field, and etc. In the last decade, there is four visual localization method. The first is the triangulation method, which using the blue and yellow color of goalpost [6]. Geometric localization using Hough transform and identification through the blue and yellow line of goalpost has been proposed in Lima et al. [7]. Then error optimization between detected field line and the virtual map

has been introduced in Neves et al. [8]. However, the first and second approach cannot be implemented since the blue and yellow color of the goalpost and the background. The last option using error optimization is in computation.

In this paper, the localization of a soccer robot through Omni-vision with particle filter is discussed. In section II, the visual information processing and particle filter are developed. In visual information subsection, the soccer field landmark identification using feature extraction and segmentation through Omnivision is developed. In section III and IV, the result discussion and conclusion are discussed.

2. Color-based landmark recognition

The importance of using an Omni-vision in soccer robot is allowing to acquire 360 degrees view around its central rotation axis. The omnidirectional vision system is provided by the hyperbolic mirror mounted on the top of the camera shown in Fig. The Omni-vision system allows obtaining object in the field around the robot without moving itself or its camera. An Omni-vision system assures an integrated perception of all landmark objects in the surrounding area of the robot, allowing more maneuverability.


Figure 1. Omni-vision camera setup.

The smoothing process is the first step to reduce noise and obscure details on images. Gaussian blur is commonly to improve the structure of the image on a specific scale. After the smoothing the image, the color space is converted from RGB to HSV and HSL, which describing color naturally and similar way. The HSV color space is to accommodate the green field landmark and ball object, then the HSL for white line object.

Thresholding process usually used in image color segmentation. Using thresholding process, the desired color interest will be separated with other colors. Pixels with a value between the minimum and maximum threshold values of the object interest will be labeled and colored with a specific value.

$$Dst(x,y) = \begin{cases} ball & ball_{min} < HSV(x,y) < ball_{max} \\ field & field_{min} < HSV(x,y) < field_{max} \\ line & line_{min} < HSL(x,y) < line_{max} \end{cases} \quad (1)$$

In the soccer field, three main objects have a different color, such as ball, field, and line. Those objects have far enough distance in HSV color space. Thus, the thresholding process in HSV color space can be applied for object detection in soccer field which described in (1). The complete process of landmark recognition is described in Figure 2.

The next step after the landmark color thresholded is scanline process to detect the landmark contour as a sensor model in the particle filter. A radial scanline is a line that starts at the center of the robot, with some angle, and ends at the limits of the image. The distance scanning from radial scanline process then calculated the real distance between the object and the center of the robot. This process needs the calibration method because of the spherical image resulting from the hyperbolic mirror. The Neural Network model is used to calibrate the correct distance, which wholly described in Setyawan et al. [1].
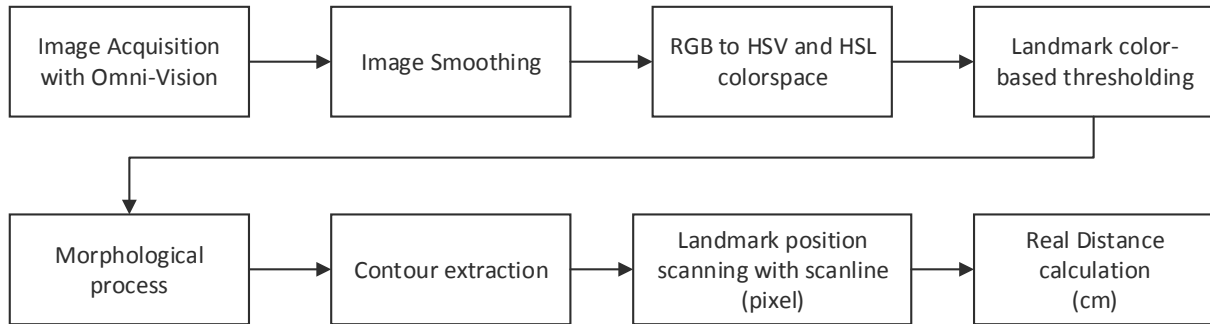
Figure 2. Soccer field landmark recognition.

3. Particle filter localization

3.1. Initialization
The particle is initialed as the "hypothesis" of the robot's position and the weight value of the position hypothesis. Since at the start of the algorithm, there is no initial information, the particle is uniformly distributed.

$$Bel(x_t, y_t, w_t) = [x_{t,n} \quad y_{t,n} \quad w_{t,n}] \tag{2}$$

Then the position is updated based on its weight on each i-iteration.

3.2. Motion model
In each cycle the control system of the robot gets new position information from odometry sensors and other external sensors such as OmniVision visual sensors. Variable changes in odometry are included in the motion model, which can be described by the following equation (**3**).

$$x_n(t) = x_n(t-1) + \Delta x_n(t) + v_n(t)$$
$$y_n(t) = y_n(t-1) + \Delta y_n(t) + v_n(t) \tag{3}$$

where $(x_n(t), y_n(t))$ is the robot position at t-iteration $(x_n(t-1), y_n(t-1))$ and $(\Delta x_n, \Delta y_n)$ is velocity data from rotation sensors.

3.3. Sensor model
The sensor model is defined by the line that is detected through the scanline command described in eq. (**4**). Then the lines are used as weights for each particle which is the hypothesis of the actual position of the robot. The weight is described as the average value of the detected distance of the line in the position hypothesis in the eq (**5**).

$$Dl_m = \left\| (x_{t,n} - x_{t,m}), (y_{t,n} - y_{t,m}) \right\|^2 \tag{4}$$

$$w_n = 1 - \frac{1}{M}\left[\sum_{m=1}^{M} Dl_m(x,y)\right] \tag{5}$$

$$w_{fast} = w_{fast} + a_{fast}(w_n - w_{fast}) \tag{6}$$

$$w_{slow} = w_{slow} + a_{slow}(w_n - w_{slow}) \tag{7}$$

Based on the equation the particle which approaches the actual position will have a significant weight.

3.4. Resampling
At the time of resampling or reshaping the particle to the position according to the latest weight is described in equation (8).

$$[x_{t,n} \quad y_{t,n} \quad w_{t,n}] = \begin{cases} [rand_n \quad rand_n \quad rand_n] & if \left(rand \left(1 - \frac{w_{fast}}{w_{slow}} \right) = 1 \right) \\ [x_{t,n} \quad y_{t,n} \quad w_{t,n}] & else \end{cases} \tag{8}$$

The probability value of the particle is directly related to the weights of the particle.

3.5. Pose estimation
Then after the resampling process is complete, the estimated position is obtained from the average weight multiplied by the previous particle hypothesis.

$$(\hat{x}(t), \hat{y}(t)) = \frac{1}{N} \sum_{n=1}^{N} [x_n(t) \quad y_n(t) \quad w_n(t)] \tag{9}$$

4. Result and discussion
The Experimental setup is using core i5 computers with 4 Gb of ram. In this test the center of the field is determined as the 0 points of the Cartesian coordinates. At the beginning of the PFL algorithm scatter particles which are shown with black dots as a hypothesis at all positions in the field coordinates of 600 particles.
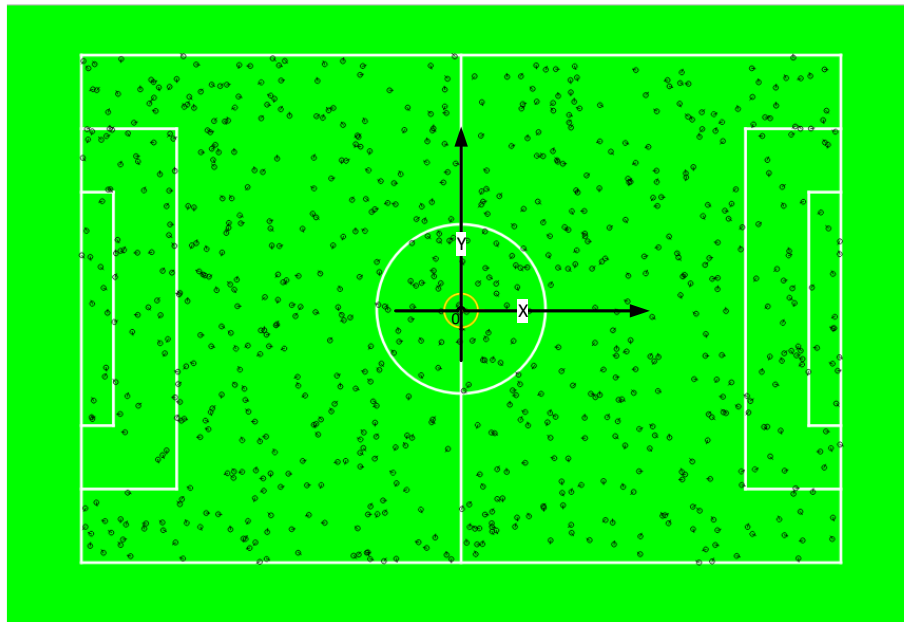

Figure 3. Particle initialization.

Then after the landmarks of the field line are detected by the scanline algorithm as in Figure 4 then each particle is calculated by weight, which then calculates the average position in accordance with the detected landmarks. After the calculation process is complete then the particles will converge at one point in accordance with the position of the detected landmarks. In Figure the particles converge around the point (-50, -255) and the average value of the particles is at that position which is indicated by the circle in blue. Furthermore, the test is carried out by moving the robot on the x-axis to find out whether the particles can follow the robot's movement or not. In Figure 5 shows the particles can follow the movement of the robot and converge at point (50, -255).
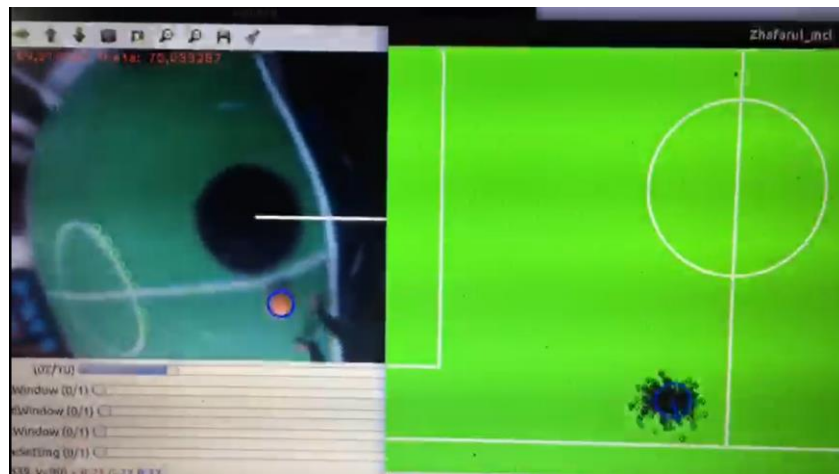
Figure 4. The convergence of particle at (-50,-255).
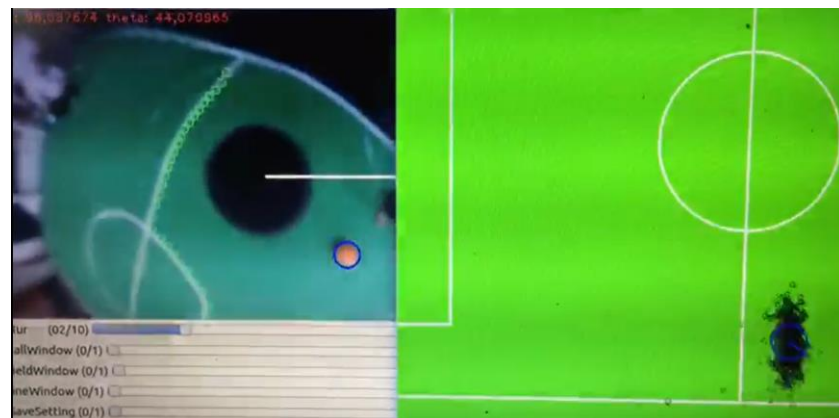
Figure 5. The convergence of particle at (50,-255).

In Figure 6 show testing at essential points such as near the goal. In the middle of the field and next to the field which are the fital points for the robot to find out the position where the robot is located. In Table 1 is the test data on several robot positions from the test results obtained an average error value of 15% is caused by noise that occurs when detecting the line landmarks that results in inaccuracies when estimating positions.
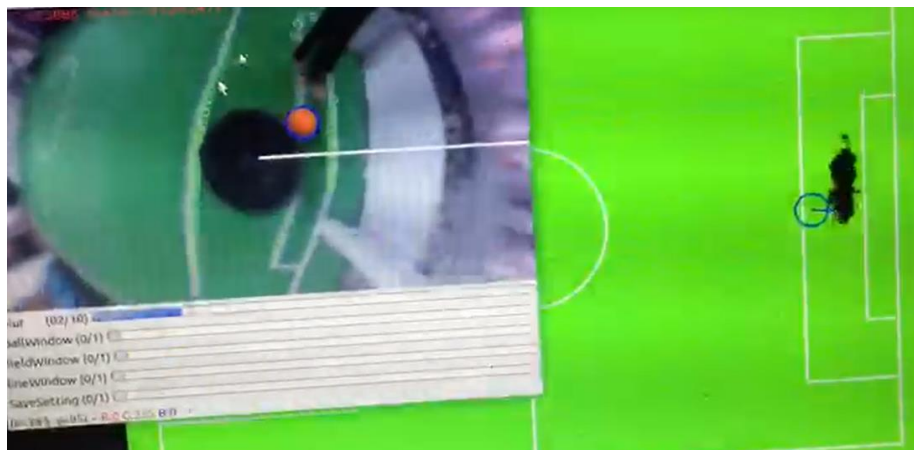
Figure 6. Localization with the robot moving around the goalpost.

Table 1. Experimental result in an arbitrary position.

Actual Position		Estimated Position	
X robot	Y robot	X estimated	Y estimated
-50	-200	-45	-209
-50	-250	-53	-240
50	-200	54	-190
50	-250	57	-240
100	-100	110	-110
100	-150	108	-140
150	0	140	7
150	-50	139	-49
200	0	190	2
200	-50	210	-40

5. Conclusion

In this paper the autonomous mobile soccer robot localization through Omni-vision has been developed. The landmark of the field has been recognized using some image processing. Furthermore, the vision sensor information used as the sensor model in the Particle filter localization algorithm. According the experimental result, Particle Filter Localization is efficient way for soccer robot localization. The Particle Filter Localization can also estimate the position accurately.

Acknowledgment

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