Localization of Wheeled Soccer Robots Using Particle Filter Algorithm

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Abstract—Localization is a method used to determine the position of an object. In mobile robots, especially wheeled soccer robots, determining the location of robots against landmarks is needed. It can determine the movements and strategies of soccer robots in a game. There are several methods can be used for localization, namely the odometry method and the extended Kalman filter. But the methods are strongly influenced by the results of reading sensors and tire slips on the robots. In this article, we proposed a particle filter algorithm for localization of wheeled soccer robots. This particle filter method is suitable for non-linear, non-Gaussian systems, and can be used in a real-time environment. We applied the particle filter algorithm to localize the position of the wheeled soccer robot. The particle filter algorithm generally has three basic stages, prediction stage, weight update and resampling. As initialization process, the particles are spread randomly or around the initial position of the robot. The prediction stage is done during the robot movement using a motion model applied to each particle. After that, the weight of each particle is updated based on the likelihood of particle data to the robot data. The resampling step is performed to update the weight of each particle. Particles with the smallest weight value will disappear by themselves and particles with large weight will retain. The position presumption is obtained through the estimation process that is by averaging the position of all particles. The experiment is done using simulation on the field with 450 *x* 300 pixels or 900 *x* 600 cm which each pixel represent 2 cm on the real soccer for competition. The particles used in the experiment are 100, 200, 400, 800, and 1600 particles. The experiment results show the satisfied result with number of particles error is 100 particles and the error is between 0.363 cm and 23.055 cm.

Keywords—wheeled soccer robot, localization, particle filter algorithm, optimization

I. INTRODUCTION

Indonesian Wheeled Robot Contest (KRSBBI) is one of the divisions of the Indonesian Robot Contest. In the KRSBBI division, two teams of robots play football based on the rules of the RoboCup Middle Size League (MSL). Each team consists of 3 robots (1 keeper and 2 attackers). The robot is equipped with an omni-vision unit, front camera, PC/linux and others. The goal of this match is the victory achieved by each team based on the number of goals.

The KRSBBI is hold every year and followed by various universities in Indonesia. The Polibatam team has participated in the KRSBI since 2017. The Polibatam team always develops the soccer robots not only in the mechanical side but also in robot strategy and optimization. One of strategies is the ability of robots to pass the ball between one robot and another. This capability requires each robot to know the robot's position information on the field. In the previous competition, the Polibatam team did not use methods/ algorithms to determine the position of the robot on the field. So the games carried out by the Polibatam team are still less effective.

Several algorithms for robot localization have been proposed previously. Pizarro et al [1] proposed localization of mobile robots using odometry and vision sensor. Their study proposed a metric reference using odometry sensor inside the robot. The Bayesian approach is used to estimate the measurement and pose of the robot. Similar study have been proposed by Codas et al [2]. Their approach combined odometry and RFID technology. The RFID is used to measure the localization based on observation model. Both of the approach successfully obtained the localization of the mobile robot. However, the error is still remain especially when there occlusion between robot. The related studies have been proposed using any combination of odometry and vision [3-5].

The stochastic method to estimate the position of the object has been proposed in many articles. The method uses the state space to model the motion of the object using Kalman filter [6] and Particle filter [7-9]. The popularity of the methods gives the challenges to many researchers to develop into many area of the research. Related to localization of the mobile robot, there are many studies have been proposed in the past. The combination of Kalman filter and visual sensing is used to localize the position of the robot is proposed in many studies [10-12]. The implementation of Kalman filter introduces to delay in the systems processing. Kalman filter also depends greatly on the prediction model, an error in creating the prediction model will surely cause all the output data to be deviated from the required reference data. Another approach is introduced using particle filter [13-15]. The particle filter approach successfully overcomes the disadvantage of Kalman filter algorithm. The particle filter approach can be a solution for non-linear and no-Gaussian system and can be implemented in the real environment. Therefore the approach can be implemented to the localization of mobile robot though the approach still has challenge to be continuously improved. Based on this challenge, in this article we implement the particle filter algorithms on wheeled soccer robot and perform a localization using three variables on robot position such as *x* and *y* position and orientation.

II. METHOD

Particle filter algorithm is popular algorithm to predict the next state based on the previous state. We proposed the particle filter algorithm to predict the position and orientation of the wheeled soccer robot. The prediction is performed

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using a number of particle spread around the robot position. Each sample of particle is represented into three parameters such as x, y and θ which represent position and orientation, respectively. The overall procedure of our proposed method is described in Fig.1.

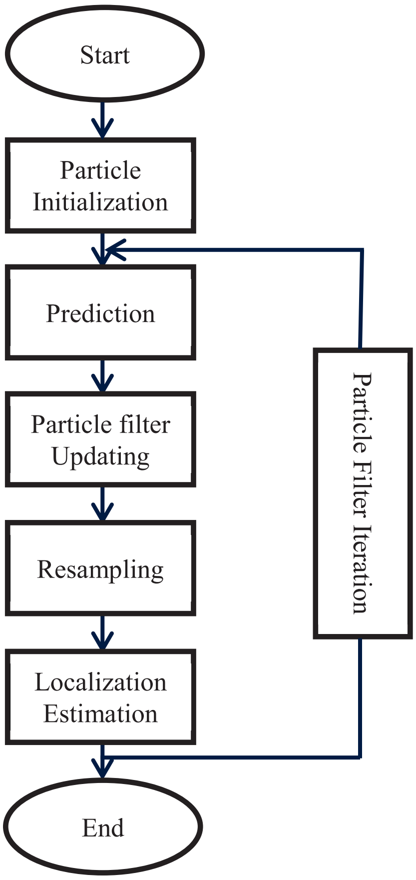

Fig. 1. Flow-Chart Particle Filter Algorithm

A. Particle Initialization

In this stage, the particles are initialized randomly on entire scene based on normal distribution (Gauss distribution) with same weight. Once the particles are spread, the particles will be predicted and weighted based on the likelihood criteria on the resampling stage.

B. Prediction

The prediction stage is done based on motion model of the robot. The model consists of position and orientation of the robot. The motion model is described on (1),

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \begin{pmatrix} \dot{x} \\ \dot{y} \\ \dot{\theta} \end{pmatrix} + \begin{pmatrix} \xi_x \\ \xi_y \\ \xi_\theta \end{pmatrix} \tag{1}$$

where x', $y'$and θ' are the position and orientation of each particle to be predicted, x, y and θ are the current position and orientation of each particle, $\dot{x}, \dot{y}, \dot{\theta}$ are the change of the current position and orientation of each particle, ξ_x , ξ_y and ξ_θ are *random Gaussian noise* for position and orientation of each particle, respectively.

C. Weight Update

The weight of each particle is obtained from the distance of the particles to the given landmark. The distance of each particle against the landmark is defined using (2)

$$\begin{pmatrix} d_x \\ d_y \\ d_\theta \end{pmatrix} = \begin{pmatrix} x - x_{lm} \\ y - y_{lm} \\ \theta - \theta_{lm} \end{pmatrix} \tag{2}$$

x, y and θ are represented position and orientation of the particle, respectively. x_{lm}, y_{lm} and θ_{lm} represent position and orientation of the landmark, respectively.

The particle weight is calculated using (3)

$$w_i = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[\frac{d_i{}^2}{2\sigma^2}\right] \tag{3}$$

w_i is the weight of each particle, σ is adaptation constant of particle filter and d_i is the distance of each particle to the landmark, respectively.

D. Resampling

The resampling process is performed to obtain new group of particle based on their weight. The particle with a high weight may continue to next iteration, while particle with relative low weight may be ignore and will disappear on the next iteration. In this process, the similar particle will occupy same position and orientation and make a copy to each other. The position and orientation of the particle will approach the position and orientation of the robot.

E. Estimation

The position and orientation of the robot is estimated based on the average of the position and calculated as (4),

$$x' = \frac{1}{N}\sum_{i=0}^{N} x_i$$

$$y' = \frac{1}{N}\sum_{i=0}^{N} y_i \tag{4}$$

$$\theta' = \frac{1}{N}\sum_{i=0}^{N} \theta_i$$

III. Experimental Result

A. Experimental Setup

The experiment was done using simulation on the field with 450 x 300 pixels or 900 x 600 cm which each pixel represent 2 cm on the real soccer for competition. The particles used in the experiment are 100, 200, 400, 800, and 1600 particles. The simulation field is describe on Fig.2. A represents a field of soccer robot with 450 x 300 pixels or 900 x 600 cm. B represents as position of robot in x and y coordinate with unit of cm. E, F and G represent position of landmark, position and translation of the robot speed, respectively. C represents the result of estimation and the error is represented by D. Start and Stop button are represented in H and I, respectively.

As initialization (Fig. 3), we give a value of robot translation in x, y and θ with 2 on each. it can be seen that particles are scattered randomly. In the first iteration, particle positions still spread with the uniform weight. Gradually, after some iteration, some particles will have different weight based on the distance to the landmark. Particles with a high weight is represented in the circled area.

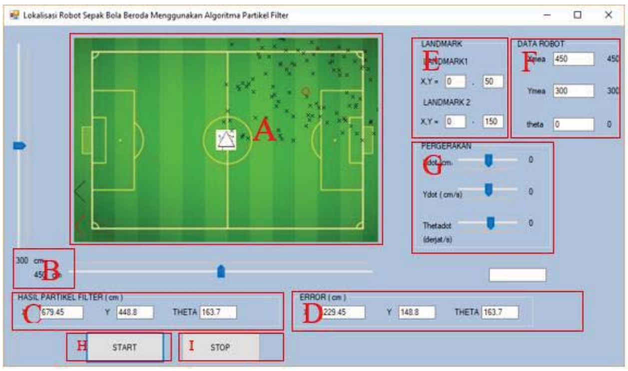

Fig. 2. The field of simulations

Fig. 3. Localization process in first iteration

Figure 4 shows the position of particles after ten iterations. The particles will approach the robot and will estimate the motion of the robot. Finally, the process will repeat until the particles converge and have a small position estimation error as shown in Figure 5 and Figure 6.

Fig. 4. Localization process after 10 Iterations

Fig. 5. Localization Processes in 15 Iterations

Fig. 6. Localization in 20 Iterations.

B. Results

Experiments were carried out with changing the variable on translation between 1 to 5 units ($\dot{x}, \dot{y}, \dot{\theta}$). Each experiment produces 24 data. The data were taken after 50 times iteration. Experiments were carried out 5 times with different number of particles (100, 200, 400, 800 and 1600 particles). Tables 1 to 5 show the average error of position and orientation of the robot. Table 1 shows that the error on x position is greater than the y position. This is because it involves the translation of robots in x position. Table 2 shows that the error on y position is greater than the y position. This is because it involves the translation of robots in y position. Table 3 shows that the error on θ orientation is greater than the x and y position. This is because it involves the change of orientation of the robots. Table 4 shows the average error when all variable is given. It shows that the error on each parameter increase. It is because the estimation of the robot is affected by translation and orientation. It shows also the comparison of the processing time against number of particles filter.

TABLE I. AVERAGE ERROR WHEN TRANSLATION ON X IS GIVEN

Particle Amount	Average Error (cm)		
	x	y	θ
1600	22.146	0.377	0.561
800	22.655	0.477	1.016
400	22.188	0.417	0.978
200	22.291	1.063	1.288
100	21.702	1.123	1.615

TABLE II. AVERAGE ERROR WHEN TRANSLATION ON Y IS GIVEN

Particle Amount	Average Error (cm)		
	x	y	θ
1600	0.410	22.324	0.756
800	0.530	22.184	0.749
400	0.363	22.192	0.960
200	0.525	22.115	2.062
100	0.505	22.178	1.353

TABLE III. AVERAGE ERROR WHEN THETA IS GIVEN

Particle Amount	Average Error (cm)		
	x	y	θ
1600	0.447	0.574	22.292
800	0.718	0.375	22.174
400	0.496	0.939	22.785
200	1.313	1.793	20.711
100	0.660	0.585	22.733

TABLE IV. AVERAGE ERROR WHEN EACH VARIABLE IS GIVEN

Particle Amount	Average Error (cm)			Processing time (ms)
	x	y	θ	
1600	22.395	22.247	21.981	5583.67
800	22.569	22.515	21.973	5596.83
400	21.763	21.818	22.383	5570.33
200	21.529	22.999	21.058	5558.50
100	21.758	21.923	23.055	5561.83

The average error of the simulation is between 0.363-23,055 cm. Average error increases when there is a disturbance with the translation in x or y position and also in the orientation. It is because, the particle filter always iterate until getting the estimation with smallest error. However, when the robot stops in a while, each sample has a small error because the robot does has fixed position to be estimated by the particle filter.

Based on the experiments, the number of particles cause CPU usage increases. The more particles is given, the CPU usage will be increased in each iteration. However, as we obtained from experiment, the number of particles was not able to reduce errors.

Table 5 shows the effect of predicted scale to the algorithm. It can be seen that the high prediction scale can increase the error. It is because the predictive scale are used in the weight update process which can generate error in calculation. So the greater the value of the prediction scale, the greater the error will be. This prediction scale is used for appropriate translation of visualization.

TABLE V. EFFECT OF PREDICTION SCALE

prediction scale	error (cm)		
	x	y	Theta
1	4.29	2.63	1.11
3	10.17	11.4	15.51
5	18.5	19.05	22.1
7	28.59	30.13	29.6
10	44.37	43.7	42.98

IV. CONCLUSION

The localization of the wheeled robot soccer using particle filter has been presented in the article. The satisfied result is obtained with error between 0.363 – 23.055 cm. The experiment was simulated on the field with 450 x 300 pixels or 900 x 600 cm similar with the real field of the robot soccer competition. The optimum number of particles used in the experiment is 100 particles. This number of particles produces the small error and short processing time. The high error was caused by the motion and the change of orientation of the robot.

The implement of particle filter algorithm for real wheeled robot soccer localization still has challenge to be improved, especially to decrease the error when the robot has the large motion and the change of orientation. The particle filter is not effective to localize the robot because of long processing time. The long processing time makes delay to the particle filter to estimate the correct position and orientation of the robot. These problem still remain for the next future work.

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