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Object Detection of Omnidirectional Vision Using PSO-Neural Network for Soccer Robot

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***Abstract*—The vision system in soccer robot is needed to recognize the object around the robot environment. Omnidirectional vision system has been widely developed to find the object such as a ball, goalpost, and the white line in a field and recognized the distance and an angle between the object and robot. The most challenging in develop Omni-vision system is image distortion resulting from spherical mirror or lenses. This paper presents an efficient Omni-vision system using spherical lenses for real-time object detection. Aiming to overcome the image distortion and computation complexity, the distance calculation between object and robot from the spherical image is modeled using the neural network with optimized by particle swarm optimization. The experimental result shows the effectiveness of our development in the term of accuracy and processing time.**

Keywords—Mobile Robot, Omni-Vision, Particle Swarm Optimization; Neural Network;

I. INTRODUCTION

In the robotics field, various researchers have been developed to improve the robot ability. Soccer robot competition is a real-world test for the control system, path planning, navigation sensor, and vision system research subject. In past decade, omnidirectional vision or Omni-vision system has become one most important thing in soccer robot system. Omni-vision provides 360 degrees view of the robot's surrounding environment in a single image that can be used to object detection [1], tracking [2], and localization [3].

Generally, Omni-vision system can be established in a various way, such as mechanical servo camera, the spherical lens (fisheye panorama), and hyperbolic mirror. The spherical lens is one of the more accessible and useful ways to provide the Omni-vision, because of the structure have a stable and rigid than using reflection mirror which consists two parts and is fragile [4].

Despite the advantages of full view from the spherical image, a barrel distortion makes object detection or tracking more complicated. The various method has been developed to rectify and restore using some image processing techniques [3], which make computation more complex. Besides that, some calibration technique has been proposed to estimate the correct spherical image model [2].

One artificial modeling technique to calibrate the spherical image is using Neural Network [5]. Since the heuristic method has been widely used to solve many problems [6]. In this paper, we combined PSO to optimize the neural network model to calibrate and modeling the distance between the object and the robot from the spherical image with some experimental data learning in developing an efficient Omni-vision to recognize and tracking the object.

II. VISION ARCHITECTURE AND OBJECT DETECTION

A. Spherical Lens Omnivision

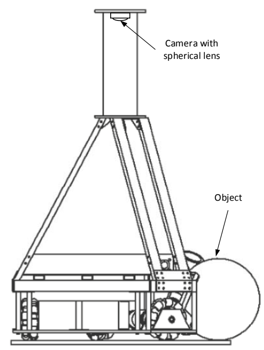

Fig. 1 Omni-vision architecture using aspherical lens

The use Omni-vision in soccer robot, allows the robot to acquire 360 degrees view around its central rotation axis. To provide effective and efficient Omni-vision system, we put the camera with spherical lens in the top of robots. This Omni-vision system allows obtaining the object in the field around the robot without moving itself or its camera.

An Omni-vision system assures an integrated perception of all main target objects in the surrounding area of the robot, allowing more maneuverability. However, it is setup implies higher degradation in resolution when the object is growing away from the robot.

B. HSV Color Space

In this study, the image captured from the camera with the spherical lens is in the RGB color space. The color components from the image are correlated with the sum of light that reflected by the object. Image segmentation of those color components will be more difficult in this situation [7].

Converting image color space from RGB to HSV color space is chosen because HSV color space describes color more naturally and similarly. According [8], all colored object in the soccer field have far enough distance in HSV color space.

C. Gaussian Blur

Gaussian blur is an image blurring process using the Gaussian function. This method is widely used to reduce noise and obscure details on images. Gaussian blur is commonly used in the early stages of digital image processing to improve the structure of the image on an absolute scale.

D. Thresholding

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

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

In the soccer field, three main objects have a different color, such as the 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).

E. Morphological

Morphological is an image enhancement process consisting of a process called opening and closing. The opening operation aims to smooth the contour of the object and eliminate all the pixels that are smaller than the elemental structure of the matrix element. The closing operation aims to smooth the contours of the object and fill the small holes with the elements of the matrix structure. [9]

Image of threshold result of HSV will be done opening and closing process. The opening is a process of erosion and then dilation, and closing is a process of dilation then erosion. Erosion aims to eliminate noise images. Dilation aims to combine the disconnected images due to the elimination of the color limit.

III. Distance estimation Using PSO-NN

A. Model of Spherical Lens

In previous steps, the distance and angle between the object and the center of the screen have been obtained. However, the distance unit still in the pixel. Therefore, real distance from the spherical image can be estimated using a neural network model. The NN model consists of one input layer, one hidden layer, and one output layer. The mathematical model from the input layer to the hidden layer described in eq:

$$\alpha_j = \sum_{i=1}^{N} WI_{i,j}X_i + WI_j^b bias_j \quad (2)$$

$$yh_j = \tanh(\alpha_j) \quad (3)$$

Then, the correlation between the hidden layer to the output layer described in eq:

$$\beta_k = \sum_{i=1}^{N} WO_{i,j}\, yh_j + WO_k^b bias_k \quad (4)$$

$$yo_k = \tanh(\beta_k) \quad (5)$$

The NN model weight $WI_{i,j}; WI_j^b; WO_{i,j};\ and\ WO_k^b$ learned by using data pair between input data such as distance in pixel and the output data such as the real distance.

B. Adaptive Particle Swarm Optimization

PSO is a population-based optimization search algorithm that inspired by birds flocking behavior. The birds are assumed to be the particle in the PSO algorithm, each particle represented as a solution, the quality of solution determined by the corresponding fitness value. The particle has the best fitness value is a leader of the group.

The algorithm of PSO begins with generating randomize particles and then each particle "fly" in the search space to search some feasible solution. In every generation, the velocity $V_{id}(t)$ and position $X_{id}(t)$ updating mechanism each particle is described in

$$V_{id}(t+1) = \omega.V_{id}(t) + c_1.r_1\big(P_{id}(t) - X_{id}(t)\big) + c_1.r_1\big(G_d(t) - X_{id}(t)\big) \quad (6)$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1) \quad (7)$$

Where $P_{id}(t)$ called personal best position, represent the best fitness value found by particle i at iteration t and $G_d(t)$ called global best, represent global fitness value found by the swarm of the particle. The constants number c_1 and c_2 called acceleration parameter, $r_1$and r_2 are independent random number distributed in range [0,1], and ω is a constant number called inertia parameter.

The main function of the inertia parameter in PSO is to maintain the proportion of exploration and exploitation in every iteration process. An adaptive inertia parameter approach in [11] is adopted in this paper. Inertia parameter updated based on the Percentage of Successful (PS) in every iteration. A high value of PS indicates the particle is moving toward an optimum solution, in contrast, the smaller value indicates that particle is moving around the optimum value without much improvement. The value of PS can calculate as follows

$$PS = \frac{\sum_{i=0}^{n} SC_i}{n} \quad (8)$$

where n is the number of particles and SC is success count of particle that defined as follow

$$SC = \begin{cases} 1 & J\big(X_{id}(t)\big) < J\big(P_{id}(t-1)\big) \\ 0 & J\big(X_{id}(t)\big) \geq J\big(P_{id}(t-1)\big) \end{cases} \quad (9)$$

Using PS, the following update rule of inertia parameter is

$$\omega = (\omega_{max} - \omega_{min})PS + \omega_{min} \quad (10)$$

C. Encoding The Particle

In the previous section, the NN model of the spherical lens has described, a correct model of the spherical lens can be obtained by learned the NN weight $WI_{i,j}; WI_j^b; WO_{i,j};\ and\ WO_k^b$. Therefore, in order to obtain the optimum model, the NN weight

$(WI_{1,1} \ldots WI_{i,j}, WI_1^b \ldots WI_j^b, WO_{1,1} \ldots WO_{i,j}, WO_1^b \ldots WO_k^b)$ becomes particle $\vec{x} = (WI_{1,1} \ldots WI_{i,j}, WI_1^b \ldots WI_j^b, WO_{1,1} \ldots WO_{i,j}, WO_1^b \ldots WO_k^b) = (x_1, x_2, \ldots, x_d)$.

D. Objective Function

The objective function is representing the error between the output of the NN model and desired data training. Using the percentage mean square error (PMSE), the best individual particle is the one which results in the minimum PMSE which described in the following equation:

$$J = PMSE = \frac{1}{M.K} \sum_{n=1}^{M} \sum_{k=1}^{K} \left(yt_{n,k} - yo_{n,k} \right)^2 \qquad (11)$$

E. Update of the personal best and global best position

Personal best position $(P_{id}(t))$ is the best position archived by particle so far and global best position $(G_{id}(t))$ is the best position archived by the swarm of the particle so far at generation. In this paper, the standard method is used to update $(P_{id}(t))$ and $(G_{id}(t))$. Since the NN model problem transformed into minimization of the objective function in (11), the following update mechanism of $(P_{id}(t))$ is

$$P_{id}(t) = \begin{cases} X_{id}(t) & J(X_{id}(t)) < J(P_{id}(t-1)) \\ P_{id}(t-1) & J(X_{id}(t)) \geq J(P_{id}(t-1)) \end{cases} \qquad (12)$$

also, the $(G_{id}(t))$ can be obtained as follows

$$G_d(t) = \min\left(J(P_1(t)), J(P_2(t)), \ldots, J(P_d(t)) \right) \qquad (13)$$

Completely path planning algorithm using adaptive Gaussian parameter is described in

Start
Initialize particle as $WI_{i,j}; WI_j^b; WO_{i,j};$ *and* WO_k^b ;
$P_i = x_i$;
End
While (termination condition is false)
  SC=0;
  For i=1 to number of particle
    For d=1 to n
      Update velocity of particle using Eq. (6)
      Update position of particle using Eq. (7)
      Evaluate particle with objective function using Eq. (11);
      End
  End
  Update P_{id} *and* G_d *using Eq. (12) and Eq. (13);*
  Update Acceleration parameter using Eq.;
  Update Inertia parameter using Eq. (10);
  Check re-initialization of particle described in Eq.
End
$(y'_1, y'_2, \ldots, y'_n) = G_d$;
End

Fig. 2 Pseudocode of proposed algorithm

IV. Experimental Result

System tested in a computer with Intel Core i5 3.2 GHz processor and 4 GB of RAM. First, we experimented with object detection such as detecting and tracking a ball and tested how far that ball can be detected. Then after that, training data taking from the real distance between the center of the robot which correlated with the center of the image and the ball.

In object detection, calculation process takes about 50 milliseconds to ball detected. With 23 cm steps, we experimented the camera detection range that can be detected the ball among 23 cm to 483 cm. Fig. 3 shows the experimental process which ball can be detected at least about 22 cm. This experiment is also obtained the correlation data between real distance and in a pixel. In Fig. 5 shows that the correlation is exponentially increased. From that figure, we conclude that the object distance can be accurately measured between 23 cm to 400 cm.

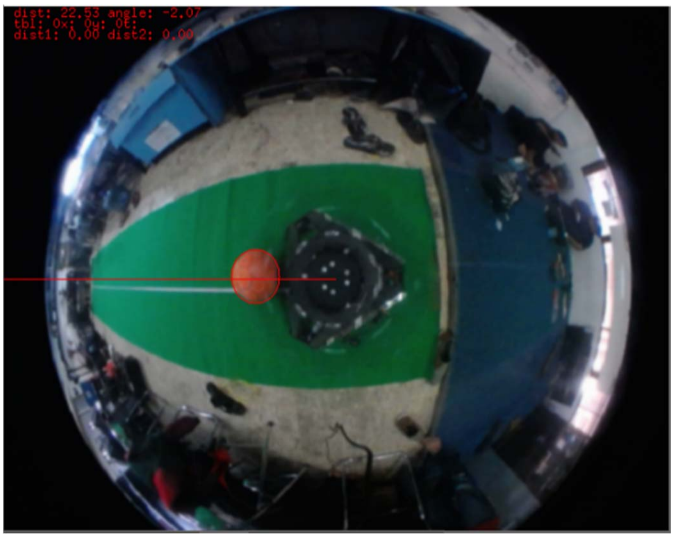

Fig. 3 Ball detection in 22 cm from the center of robot

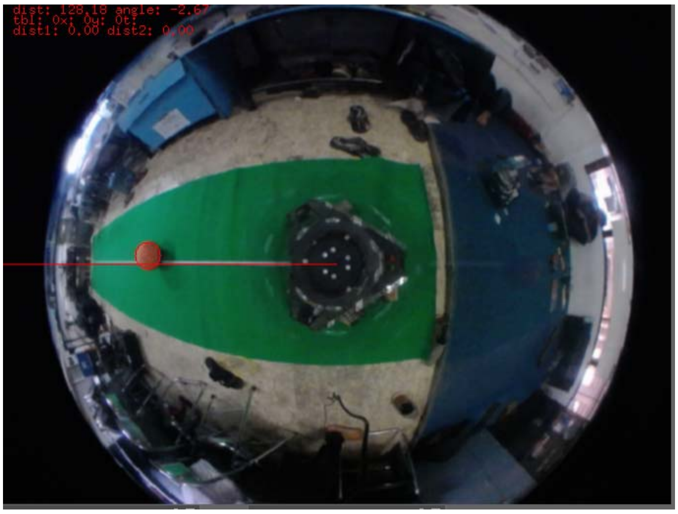

Fig. 4 Ball detection in 128 cm from the center of robot

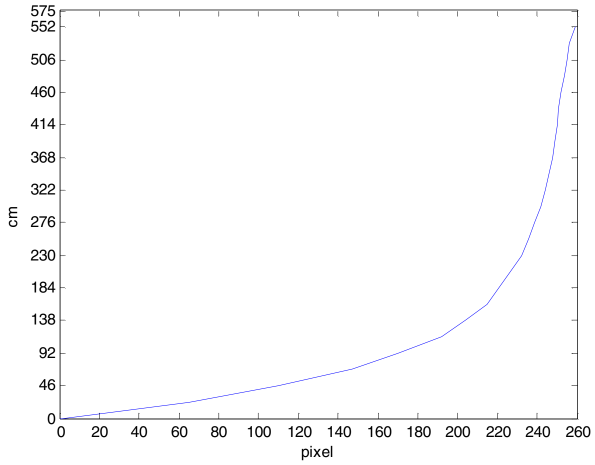

Fig. 5 Object Distance Correlation in cm and pixel

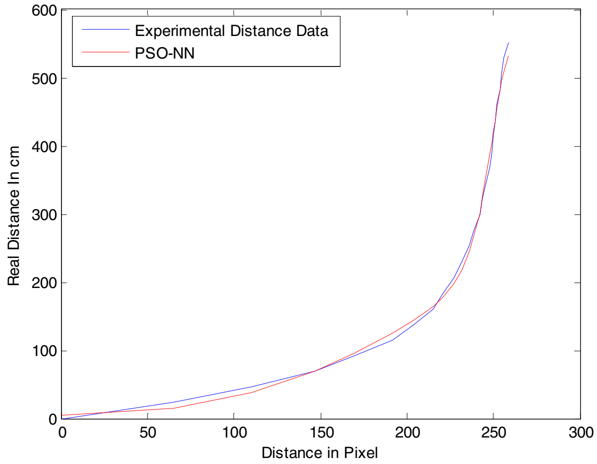

Fig. 6 Distance Comparison between experimental data and PSO-NN model

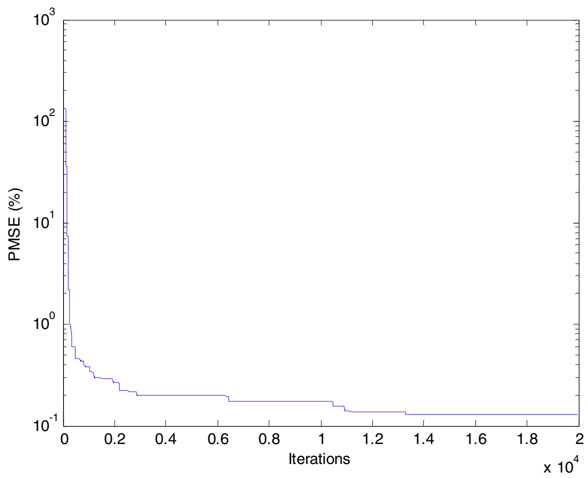

Fig. 7 objective function value in every iteration

The seconds, experimental object distance data trained by PSO to get the NN forward model. In this experiment, PSO using 30 numbers of the particle, and the acceleration parameters are $c_1 = c_2 = 2$. PSO can find the global optimum with 0.11 % of PMSE. Fig. 6 shows that the data resulting from PSO-NN accurately close to experimental data. Under the 14000 iteration PSO can find the global optimum. Fig. 7 shows the convergence speed in 2×10^4 iteration.

V. Conclusion

From the experimental data, the object in the soccer field can be detected and tracked. The real distance in cm of the object can be accurately modeled. With our proposed method the object detection and distance computation with omnidirectional vision are effective and efficient in accuracy and processing time.

VI. Acknowledgment

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References

[1] D. B. Kusumawardhana and K. Mutijarsa, “Object recognition using multidirectional vision system on soccer robot,” 2017, pp. 183–187.

[2] W. Feng, Y. Liu, and Z. Cao, “Omnidirectional Vision Tracking and Positioning for Vehicles,” 2008, pp. 183–187.

[3] H. Lu, S. Yang, H. Zhang, and Z. Zheng, “A robust omnidirectional vision sensor for soccer robots,” *Mechatronics*, vol. 21, no. 2, pp. 373–389, Mar. 2011.

[4] Z. Cao, S. Liu, and J. Roning, “Omni-directional Vision Localization Based on Particle Filter,” 2007, pp. 478–483.

[5] B. A. Garro and R. A. Vázquez, “Designing Artificial Neural Networks Using Particle Swarm Optimization Algorithms,” *Comput. Intell. Neurosci.*, vol. 2015, pp. 1–20, 2015.

[6] N. Setyawan, R. E. A. Kadir, and A. Jazidie, “Adaptive Gaussian parameter particle swarm optimization and its implementation in mobile robot path planning,” 2017, pp. 238–243.

[7] A. N. Fitriana, K. Mutijarsa, and W. Adiprawita, “Color-based segmentation and feature detection for ball and goal post on mobile soccer robot game field,” 2016, pp. 1–4.

[8] A. K. Mulya, F. Ardilla, and D. Pramadihanto, "Ball tracking and goal detection for middle size soccer robot using the omnidirectional camera," 2016, pp. 432–437.

[9] Setiawardhana, R. Dikairono, T. A. Sardjono, and D. Purwanto, "Visual ball tracking and prediction with the unique segmented area on soccer robot," 2017, pp. 362–367.

[10] J. Kennedy and R. Eberhart, “Particle Swarm Optimization,” *IEEE Int. Conf. Neural Netw.*, pp. 1942–1948, 1995.

[11] A. Nickabadi, M. M. Ebadzadeh, and R. Safabakhsh, “A novel particle swarm optimization algorithm with adaptive inertia weight,” *Appl. Soft Comput.*, vol. 11, no. 4, pp. 3658–3670, Jun. 2011.