

# Ball Position Transformation with Artificial Intelligence Based on Tensorflow Libraries

Setiawardhana

Dept of Informatic and Computer Engineering  
*Politeknik Elektronika Negeri Surabaya*  
 Surabaya, Indonesia  
[setia@pens.ac.id](mailto:setia@pens.ac.id)

Bima Sena Bayu Dewantara

Dept of Informatic and Computer Engineering  
*Politeknik Elektronika Negeri Surabaya*  
 Surabaya, Indonesia  
[bima@pens.ac.id](mailto:bima@pens.ac.id)

Rudy Dikairono

Dept of Electrical Engineering  
*Institut Teknologi Sepuluh Nopember*  
 Surabaya, Indonesia  
[rudydikairono@ee.its.ac.id](mailto:rudydikairono@ee.its.ac.id)

Afis Asryullah Pratama

Postgraduate Program Dept of Electrical Engineering  
*Politeknik Elektronika Negeri Surabaya*  
 Surabaya, Indonesia  
[afisarsy@gmail.com](mailto:afisarsy@gmail.com)

**Abstract**— Research on wheeled soccer robots has been carried out by several researchers. This is due to the existence of national and international competitions. Previous research was to create a ball position transformation system with a modified method of neural network architecture. This research was developed by building an intelligent transformation system with the Tensorflow library. This transformation system aims to be able to directly measure the distance of objects in real terms without first changing the environmental image from an omni field to a flat plane with conventional camera calibration techniques. This process can replace manual calibration with a variety of field size changes. The system can transform with mean error 0.0000026 on epoch 10000 using “conda-tensorflow-neural network” libraries. It can transform the position of the ball from the omni space to the cartesian space. This system was implemented on wheeled soccer robot as keeper.

**Keywords**—wheeled soccer robots, neural network, transformation, tensorflow

## I. INTRODUCTION

Several studies related to soccer robots, including camera sensors, have been developed. Previous researchers [1], [2], [3], [4] developed a multi-agent system for robot collaboration and coordination. These robots can work together and coordinate to provide information on the position of the ball and the team's robot. They built a robot collaboration system for the FIRA Micro-Robot World Soccer Tournament (MiroSot) match with the MIMO Fuzzy Inference Engine. The robot can achieve the expected goals based on the knowledge that is trained. Researchers are also developing mechanical and electronic systems to improve the capabilities of the robot, especially the movement of the robot itself. Researchers [5], [6] also develop a communication system between robots in a game. Transformation system [7] has been developed by modeling using ANN. The developed system requires a lot of training data (up to 10000 data). the system is used to recognize the position of the goal with the HSV method. Departing from previous research [8]–[10], the ball position estimation system and its navigation, this research creates a ball position transformation system based on the Tensorflow library. The system that has been created can be more familiarly implemented in several open source robotic systems.

## II. TRANSFORMATION WITH ARTIFICIAL INTELIGENT

### A. Wheeled Soccer Robot

This system uses a robot in the previous research [8], [9], [11], [12], namely the IRIS robot as shown in Fig. 1. The focus of this study is on developing the ability to visual perceptual camera models. The ITS' Robot Intelligent System (IRIS – ITS) robot uses an omnidirectional camera. The image obtained is in the omni plane. Robot perception will be easier if the image is transformed into a flat form or cartesian plane. The omnidirectional camera had taken a picture with 360 degree. The omni camera was used to take pictures of the environment on the wheeled soccer robot game field. The size of the field that can be reached is 600 cm x 900 cm. the camera can see the side of the field well at a size of 600 cm x 450 cm.



Fig. 1. Omnidirectional camera on IRIS robot [[8], [9]]



Fig. 2. Result of omnidirectional camera [8]–[10], [12]

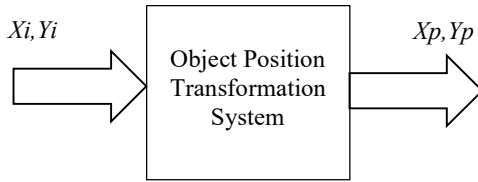


Fig. 3. Diagram for transformation system

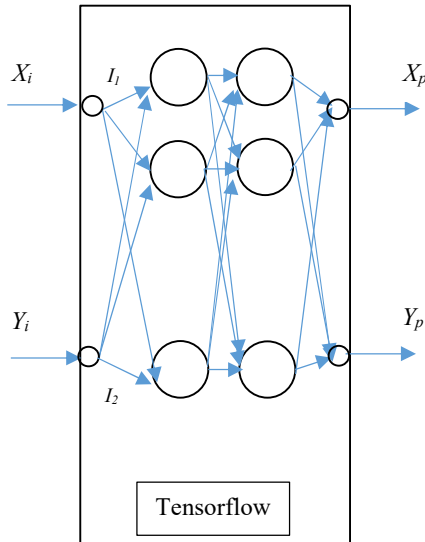


Fig. 4. Tensorflow neural network

IRIS robot using omnicaamera on Fig. 1 and the result has been sown in Fig. 2. Robot view around the game field with omnidirectional camera. The robot has difficulty obtaining visual perception information with the actual distance to the ball's position on the playing field

### B. Transformation System

The transformation system was a system created using artificial intelligence with the aim of converting the ball position from the omni plane (the resulting image from the omni plane) to the cartesian plane. The diagram system used is as shown as Fig. 3 and Fig.4. The ball transformation system based on artificial intelligence using tensorflow library.  $X_i$  and  $Y_i$  were the center of Region of Interest (ROI) of the object and  $X_p$  and  $Y_p$  were the result of position for the object on game field. The tensor flow was using neural network library for training dan testing the ball position on omni camera and cartesian area (real game field area). The system was proposed using backpropagation neural network with tensorflow. The equation concepts on equation (1) until (25).

#### Layer 1

$$I_1 = x_i \quad (1)$$

$$I_2 = y_i$$

$$O_i^{L1} = I_i \quad (3)$$

#### Layer 2

$$a_j = \sum_{i=1}^N O_i^{L1} W^{L1-L2}_{i,j} \quad (4)$$

$$O_i^{L2} = \frac{1}{1 + \exp^{-(a_j + bias_j)}} \quad (5)$$

#### Layer 3

$$b_k = \sum_{j=1}^N O_j^{L2} W^{L2-L3}_{j,k} \quad (6)$$

$$w^{L1-L2} = w^{L1-L2} + \Delta w^{L1-L2}_{i,j} \quad (7)$$

$$O_k^{L3} = \frac{1}{1 + \exp^{-(b_k + bias_k)}} \quad (8)$$

$$x_p = O_1^{L3} \quad (9)$$

$$y_p = O_2^{L3} \quad (10)$$

The backward equations:

#### Error Layer 3

$$x_p' = O_1^D \quad (11)$$

$$y_p' = O_2^D \quad (12)$$

$$Err(MSE) = \frac{1}{2} (O_k^{L3} - O_k^D)^2 \quad (13)$$

$$b_k = \partial_3 = \frac{dErr_k}{db_k} = O_K^D - O_K^{L3} \quad (14)$$

Error Layer 2

$$a_j = \partial_2 = \frac{dErr_k}{da_j} = \frac{dErr_k}{db_k} \cdot x \cdot \frac{db_k}{dO_j^{L2}} \cdot x \cdot \frac{dO_j^{L2}}{da_j} \quad (15)$$

$$Err_j = \frac{dErr_k}{db_k} \cdot x \cdot \frac{db_k}{dO_j^{L2}} = \sum_{k=1}^L \partial_3 \cdot w_{i,j}^{L2-L3} \quad (16)$$

$$a_i = \partial_2 = Err_j \cdot O_j^{L2} \cdot (1 - O_j^{L2}) \quad (17)$$

Weight Update Layer 2 to Layer 3

$$\Delta w_{j,k}^{L2-L3} = \eta \cdot \frac{dErr_k}{dw_{j,k}^{L2-L3}} = \eta \cdot \frac{dErr_k}{db_k} \cdot \frac{db_k}{dw_{j,k}^{L2-L3}} = \eta \cdot \partial_3 \cdot O_j^{L2} \quad (18)$$

$$w^{L2-L3} = w^{L2-L3} + \Delta w_{j,k}^{L2-L3} \quad (19)$$

Weight Update Layer 1 to Layer 2

$$\Delta w_{i,j}^{L1-L2} = \eta \cdot \frac{dErr_k}{dw_{i,j}^{L1-L2}} = \eta \cdot \frac{dErr_j}{da_j} \cdot \frac{da_j}{dw_{i,j}^{L1-L2}} = \eta \cdot \partial_2 \cdot O_i^{L1} \quad (20)$$

$$w^{L1-L2} = w^{L1-L2} + \Delta w_{i,j}^{L1-L2} \quad (21)$$

Weight Update Bias Layer 2 to Layer 3

$$\Delta bias_k^{L2-L3} = \eta \cdot \frac{dErr_k}{dbias_k^{L2-L3}} = \eta \cdot \frac{dErr_k}{db_k} \cdot \frac{db_k}{dbias_k^{L2-L3}} = \eta \cdot \partial_3 \cdot 1 \quad (22)$$

$$bias^{L2-L3} = bias^{L2-L3} + \Delta bias_k^{L2-L3} \quad (23)$$

Weight Update Bias Layer 1 to Layer 2

$$\Delta bias_j^{L1-L2} = \eta \cdot \frac{dErr_j}{dbias_j^{L1-L2}} = \eta \cdot \frac{dErr_k}{da_j} \cdot \frac{da_j}{dbias_j^{L1-L2}} = \eta \cdot \partial_2 \cdot 1 \quad (24)$$

Learning Rate Update

$$\eta(k) = \frac{\mu_0}{1 + \frac{k}{k_0}} \quad (25)$$

The training and testing data, (Xi,Yi) and (Xp,Yp), were obtained from real data in the robot field which was adjusted to the rules of the international robot contest.

### III. EXPERIMENTAL AND RESULT

The experimental data technique for transformation is implemented by:

1. Place the ball on the field by recording the ball position data in the omni plane (X<sub>i</sub>, Y<sub>i</sub>) and the ball position data on the actual field (X<sub>p</sub>, Y<sub>p</sub>).
2. Training was done with specific data for training using neural networks and tensorflow libraries
3. Testing was done with data specifically for testing using the neural network and tensorflow libraries

4. The total data was 5000 data. The composition of training and testing data were 1 : 1, The number of data train : 2500 data and data test : 2500 data. This experiment used 500 data train and 500 data test.

Tensorflow library was called using function for train and test the data.

for epoch in range(epochs):  
 session.run(train, feed\_dict={X: INPUT\_BALL,  
 Y:OUTPUT\_BALL})

Script 1. Train Session

TABLE I. DATA TRAIN[8]

No	Input		Output	
	$x_i$	$y_i$	$x_p$	$y_p$
1	0.030556	0.055000	0.130098	0.050508
2	0.033333	0.110000	0.118719	0.101368
3	0.038889	0.085000	0.127967	0.059764
4	0.038889	0.140000	0.126923	0.101302
...	...	...	...	...
2500	0.777778	0.820000	0.893107	0.849109

TABLE II. DATA TEST[8]

No	Input		Output	
	$x_i$	$y_i$	$x_p$	$y_p$
1	0.033333	0.090000	0.109154	0.065141
2	0.038889	0.110000	0.147659	0.074936
3	0.041667	0.135000	0.148264	0.095533
4	0.041667	0.155000	0.134280	0.092174
...	...	...	...	...
2500	0.775000	0.825000	0.888170	0.856469

TABLE III. RESULT : EPOCH AND ERROR

No.	Epoch	Mean Error
1	1000	0.160000
2	2000	0.000060
3	3000	0.000012
4	4000	0.0000067
5	5000	0.0000046
6	6000	0.0000037
7	7000	0.0000032
8	8000	0.0000029
9	9000	0.0000027
10	10000	0.0000026

The program was built using neural network with tensorflow function. The process as shown as Fig. 5. Table I and Table II were the data for train and test a neural network transformation system. The data for mean error as shown as Table III.

```

0.16183288
6.0533202e-05
1.2989644e-05
6.717022e-06
4.680294e-06
3.7296297e-06
3.2122698e-06
2.910622e-06
2.7286076e-06
2.6178093e-06
Training For Ball Position Transformation Complete
[[0.13068879 0.0499247 ]
[0.12350002 0.11940005]
[0.14306396 0.08985186]
...
[0.8458066 0.7645534 ]
[0.8864 0.8541 ]
[0.00187427 0.00226006]]

```

Fig. 5. Train and test with conda-tensorflow

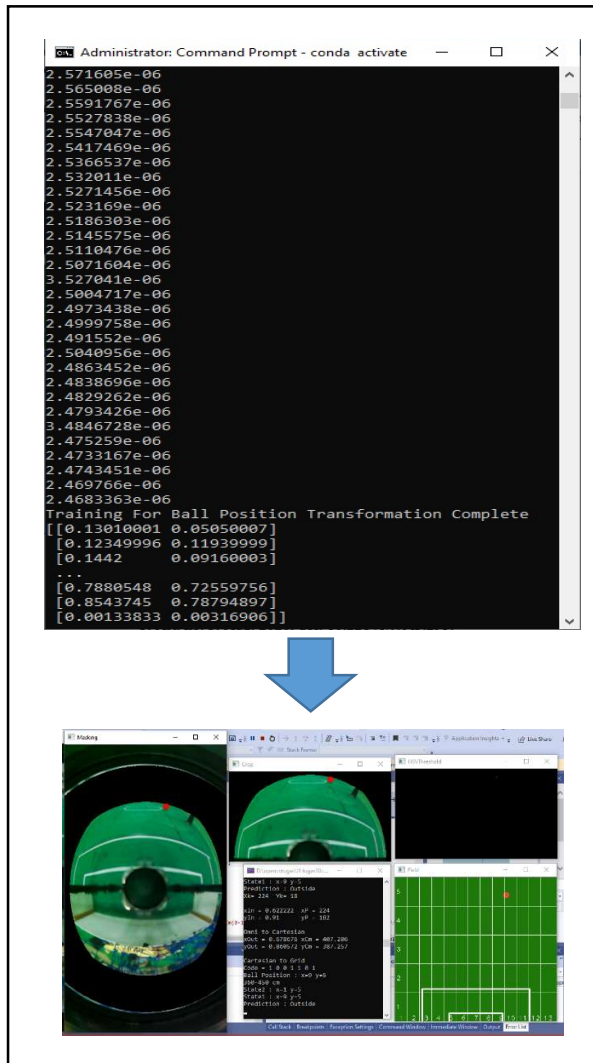


Fig. 6. Transformation visualization

The process for transformation run on memory behind the main program. The main program fetches data with timer every 200ms.

#### IV. CONCLUSION

We have developed for ball position transformation system that used for IRIS robot. The system is used to transform the position of the ball on the omni-shaped screen to the flat plane of the playing field in actual size. The transformation system is built using artificial intelligence and consists of 1 input layer, 1 hidden layer and 1 output layer. the system is trained with as many training epochs as 10000 and get results with an average error of 0.0000026. The implementation of this artificial intelligence system is called using a timer every 200 ms by the main system consisting of a camera system and a navigation system.

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