Robust Camera Calibration for the MiroSot and the AndroSot Vision Systems Using Artificial Neural Networks

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Abstract. The MirosSot and the AndroSot soccer robots have the ability to recognize, and navigate within, their environments without human intervention. An overhead global camera, usually at a fixed position, is used for the robot's vision. Because of the lens distortion, images obtained from the camera do not accurately represent the robot's environment. The distortions affect the coordinates. A technique to calibrate the camera is required to transform the skewed coordinates of the objects in the image to the physical coordinates, which define their real-world position. In this study, a method is proposed for camera calibration using an artificial neural network (ANN) in a two-step process. First, ANN was used to select the camera height and the lens focal lengths for high accuracy. Second, ANN was used to map a coordinate transformation from the camera coordinates to the physical coordinates. During the learning process, the weight of each node in the ANN model changed until the best architecture is reached. The experiments thus resulted in an optimum ANN architecture of 2×4×25×2. The accuracy and efficiency of the camera calibration method were obtained by relearning using the ANN whenever changes to the environmental occurred. Relearning was done using the new input data set for each respective environmental change. Based on our experiments, the average transformation error of the calibration method, using many types of camera, camera positions, camera heights, lens sizes, and focal lengths, was 0.18283 cm.

Keywords: Camera Calibration Technique, Neural Network, Robot Soccer, Global Vision System.

1 Introduction

If the camera is not positioned exactly over the target, the environment will cause the image projection to be distorted and asymmetric. The camera height and position will

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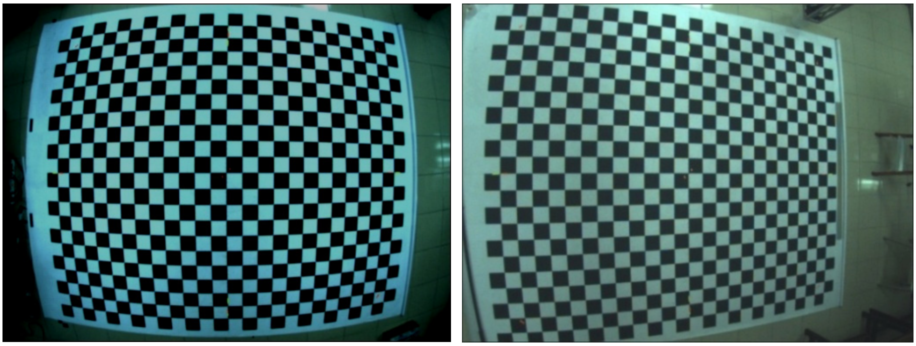
affect the resulting image projection. As the distance of the objects from the center of the camera increases, the differences between the positions of the detected objects from those of the real objects become greater. Objects photographed by a camera in the perpendicular direction will be more accurate projections, whereas if the object is photographed by a camera at an inclination, larger differences in the image projection will occur [1].

The coordinate transformation process is influenced by the type of lens, the height of the camera and the position of the camera. Fig 1 shows the difference in the image projection when the camera is located off-center with respect to the position of the object. The primary issue with respect to lens distortion and camera position is finding an accurate transformation to obtain the actual robot position from the camera projection.



(a) (b)

Fig. 1. (a) An image object photographed by a camera from the perpendicular direction, (b) an image object photographed by a camera from 100 cm from the center of the field

Camera calibration is used to transform the object position into the actual position. Camera calibration with a view obtains the detailed information from the camera. Camera calibration from the image itself is the primary problem in computer vision [2]. Additionally, camera calibration is the primary process in computer vision used to determine the actual position of the robot from an image [3, 4, 5] Camera calibration in a mobile robot vision system is used to transform the robot position in the camera image to its physical position. The objective of the camera calibration method used in our study is to resolve the non-linear lens distortion using artificial neural networks.

2 State of the Art

2.1 Calibration Grid

A transformation system is calibrated by comparing an object that has a known position in the physical coordinate system to its camera coordinate system position [6, 7, 8]. The transformation process from camera coordinates into physical coordinates requires measurement accuracy and precision [9, 10]. The measurement accuracy of the transformation process is determined from the mass errors that result from the transformation process on the actual object position in the physical coordinates [11]. The camera calibration process also requires a reference point from the image, which is the manifestation of an actual point in the real world [8, 12]. The calibration process is facilitated by the availability of a calibration grid. An example calibration grid is shown in Fig. 2. National Instruments provides limitations that must be met in the construction of a calibration grid as follows [1]:

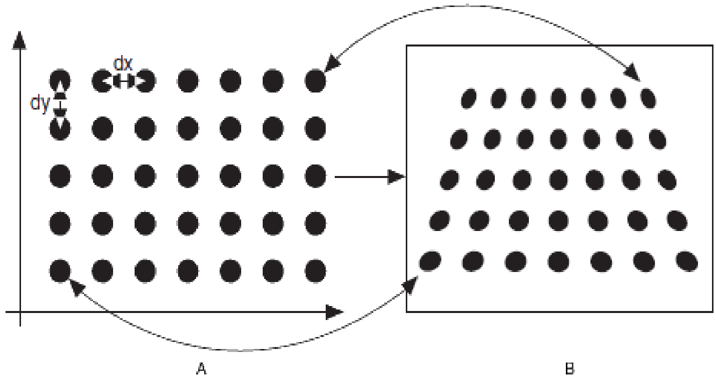


Fig. 2. Calibration process requires a reference point to transform physical coordinates into camera coordinates (http://zone.ni.com/reference/en-XX/help/372916J-01/nivisionconcepts/spatial_calibration/)

1. The distances between points in the x and y directions are the same.
2. The dots must fill the entire workspace.
3. The distances between points are the same.
4. The cutoff distances between the centers of the dots are the same.
5. The dots should be in vertical columns and horizontal rows that are perpendicular to calibrate the grid.

There are many types of grid calibration that can be used, such as grid calibration points, grid calibration chessboard, grid calibration lines, and grid calibration scale curve. From these, the most frequently used are the grid calibration points and the grid calibration chessboard.

2.2 Camera Calibration Using Artificial Neural Networks

A neural network is one of the models that simulate the learning process of the human brain [13]. The human brain consists of millions of neurons; each neuron connects one cell to another cell. An artificial neural network is a collection of nodes with the ability to learn and to store information. Based on the research conducted by [14], an artificial neural network is similar to the human brain in two ways: neural networks have the ability to acquire knowledge through a learning process and, in neural networks, knowledge storage has synaptic weight as a strength connection between the neurons.

Artificial neural networks have been implemented in various fields of science and technology, especially in robotics and image processing. Robotics and image processing are interlinked because, through image processing, a robot can see the world. According to [15], camera calibration has the same features as artificial neural networks in various areas, such as the following:

1. A neural network is developed using the properties of several non-linear neurons; therefore, artificial neural networks have the ability to train non-linear data.
2. Artificial neural networks and camera calibration use a similar training mechanism to find the coefficients from data that was previously unknown. In addition, they calculate unknown data, using an artificial neural network to determine the camera calibration model with various camera distortion models, which can reduce the linear distortion errors. They can also solve various non-linear distortion problems.

In previous studies [16, 17, 18], implicit camera calibration using a broad spectrum of layer perceptron artificial neural networks have been developed. They used two hidden layers with two input nodes and two output nodes. Input nodes in the form of x' and y' camera coordinates are transformed to x and y physical coordinate results. The first layer has ten (10) nodes while the second layer has eight (8) nodes. Learning was implemented using 5000 iterations. This study used a calibration grid point, a point column distance of 25 mm, a point row distance of 20 mm, and a calibration grid size of 11×9 (99-point calibration). The results were compared with the two-step coordinate transformation method developed by Tsai (Tsai 1987). The average error in this method was 0.6559. The neural network method reduced the error level compared with Tsai's two-stage method by as much as 11.45%.

Wang et al. [19] developed an application for the correction of distortion using an artificial neural network with standard grid plates. The standard grid was used to calculate the distortion of the camera. The standard grid was produced using lines spaced 1 mm apart. The calibration grid size in their study was 19×25. The region bounded by the intersection of the center line with the 10th and the 13th column is the center region of the camera with no distortion. The calibration process uses a back propagation artificial neural network with two hidden layers and a feed forward algorithm. Lee and Oh [20] developed a method for camera calibration using an artificial neural network to estimate the global position using a camera mounted on the ceiling. Their method uses input data in the form of pixels per image distortion with an output of pixels per image to be repaired.

3 Methodology

This section describes the approach used in this study. The camera calibration method is based on artificial neural networks, using the camera position, lens focal length, and the current condition.

3.1 Training Set Data Preparation

The provision of the training data set from the images involves several parameters, such as the type of camera, the lens size, the camera position, and the direction of the camera. The resulting image data set was used both for the development and for the experiments used in the camera calibration.

3.2 Development of the Camera Calibration Method

Objects captured by the camera are not in their actual position; therefore, a process is required to transform from camera coordinates into physical coordinates. The purpose of the camera calibration process is to acquire the physical positions of the objects from images. Development of the camera calibration method in this study uses an artificial neural network.

3.3 Camera Calibration Performance Measurements and Experiments

Performance measurements were conducted to obtain the best method for the camera calibration process. For this purpose, a series of experiments to obtain the best performance of every method is proposed. The experimental design of the camera calibration method in our study is divided into two sections: the experimental camera calibration method based on the camera type and lens type and the experimental camera calibration method based on the camera position and camera direction. The camera types that we used in this study are based on CCD-sized sensors, brand cameras, and camera drivers. The types of lenses used in our study are based on the size of lens, brand of lens, and lens focal length.

Camera Calibration Experiments Based on Camera Height and Lens Focal Length

Experimental studies of the camera calibration methods were performed for several camera heights and lens focal lengths. The experiments were conducted to determine the best artificial neural network model architecture to transform the camera image to the robot position based on camera height and lens focal length. This experiment used fifteen images obtained from a Basler Scout SCA 640-70F camera.

Camera Calibration Experiment Based on Camera Position and Orientation

Experiments were performed based on the camera position and the orientation using a Basler Scout SCA 640/120 fc, CCD Sensor Size 1⁄4 and Fujinon lens (lens size 1⁄3) camera. The set of experiments for the camera calibration method based on the camera height, the camera position, and the direction the camera was facing is shown in Table 1. The coordinates of the camera position for the set of experiments is also shown in Table 1. The camera position and orientation is shown in Fig. 3.

Table 1. Set of experiments for the camera calibration based on camera height and camera rotation

Experiment set	Camera Position	Camera Coordinates	Camera Height	Camera Rotation
Experiment 1	A1	(0,0)	240	0^0
Experiment 2	B1	(100,0)	240	0^0
Experiment 3	C1	(0,-80)	240	0^0
Experiment 4	D1	(100,-80)	240	0^0
Experiment 5	A2	(0,0)	200	0^0
Experiment 6	B2	(100,0)	200	0^0
Experiment 7	C2	(0,-80)	200	0^0
Experiment 8	D2	(100,-80)	200	0^0
Experiment 9	E	(-40,40)	220	0^0
Experiment 10	F	(40,40)	220	0^0
Experiment 11	G	(40,-40)	220	0^0
Experiment 12	H	(-40,-40)	220	0^0
Experiment 13	A1	(0,0)	220	10^0
Experiment 14	A1	(0,0)	220	-30^0
Experiment 15	A1	(0,0)	220	20^0
Experiment 16	A1	(0,0)	220	30^0
Experiment 17	G	(0,0)	220	-30^0
Experiment 18	E	(0,0)	220	-30^0
Experiment 19	F	(0,0)	220	30^0
Experiment 20	H	(0,0)	220	30^0

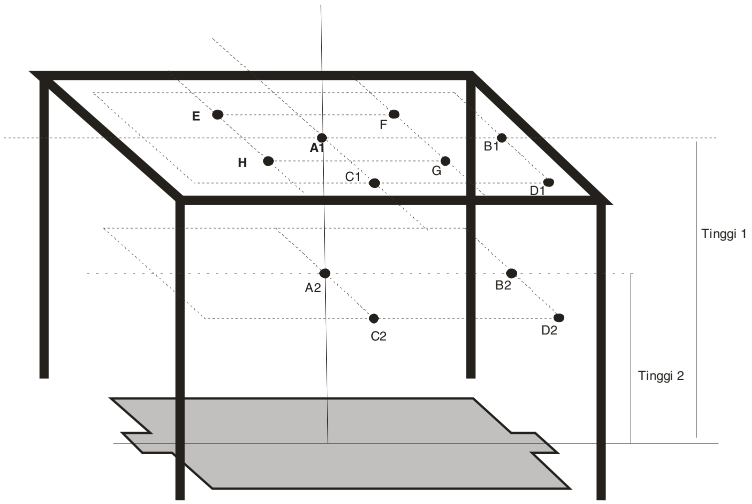


Fig. 3. Camera position

4 Results and Discussion

4.1 Artificial Neural Network Method for Camera Calibration

The development of the camera calibration method using an artificial neural network was divided into several steps as follows:

1. Determine the physical coordinates from the image.
2. Train the physical coordinates and the image coordinates using a neural network to obtain the function that will be used to transform camera coordinates into physical coordinates.
3. Determine the neural network model that is most suitable to correct for lens distortion.
4. Determine the most suitable activation function and learning rate.
5. Simulate data outputs to ensure that the method can be implemented in a mobile robot system.

4.2 Development of the Camera Calibration Method Using an Artificial Neural Network

The following section describes the development process of the camera calibration method based on the current state of global overhead mobile robot vision.

Development of the Camera Calibration Method

The camera calibration is a step in the sight of the three-dimensional (3D) computer to extract the metric information from a two-dimensional (2D) image. Camera calibration methods in our study use two input values and two output values in artificial neural networks. The parameters that are used in our study are the camera coordinates x' and y' for the artificial neural network inputs and the physical coordinates for the outputs. In this study, the results of experiments performed using artificial neural network models are shown in Table 2. The data in Table 2 show that the best ANN model is a 2×4×25×2 model with two inputs to the artificial neural network as camera image coordinates (x', y'), four nodes in the first hidden layer, twenty five hidden nodes in the second layer, and two outputs for the physical coordinates as the result. The resulting artificial neural network model is shown in Fig. 7. The previous study by Woo and Park [17,18] used a 2×10×8×2 artificial neural network model with two inputs, ten hidden nodes in the first layer, eight hidden nodes in the second layer, and two nodes for the output. The study reported in [15] uses a 2×5×2 artificial neural network model, i.e., with two inputs, five hidden nodes and two output nodes. Both of these prior methods used back propagation techniques.

The coordinate transformation process was implemented by calculations performed on the detected position of the robot using weights derived from the ANN learning. Some examples of images used in the development and testing of the camera calibration method based on the current condition are shown in Fig. 4. Results of the coordinate transformation from the image using the ANN method are shown in Fig. 5.

Table 2. Results of the development tests of an ANN architecture using two inputs and two outputs with the Levenberg–Marquardt learning algorithm

Test No	Architecture RNB	Learning Time	Average Error (ΔX, ΔY)		Maximum Error (ΔX, ΔY)	
			X	Y	X	Y
1	2-8-4-2	0:00:55	0.3821	0.2642	3.3068	2.646
2	2-4-8-2	0:06:47	0.6755	0.4295	3.3000	2.1950
3	2-8-16-2	0:08:26	0.2406	0.1912	5.0200	2.2140
4	2-16-8-2	0:21:57	0.6422	0.5623	2.4200	3.2640
5	2-8-24-2	0:27:44	0.3982	0.2555	3.0700	2.2610
6	2-4-25-2	0:05:10	0.1539	0.1346	1.9800	1.1760
7	2-25-4-2	0:48:32	0.5718	0.4249	2.5470	2.6410
8	2-24-8-2	0:37:39	0.5460	0.7868	2.9205	2.3317

Note: ANN Model $2 \times 4 \times 25 \times 2$ using two inputs is the best model from the ANN testing

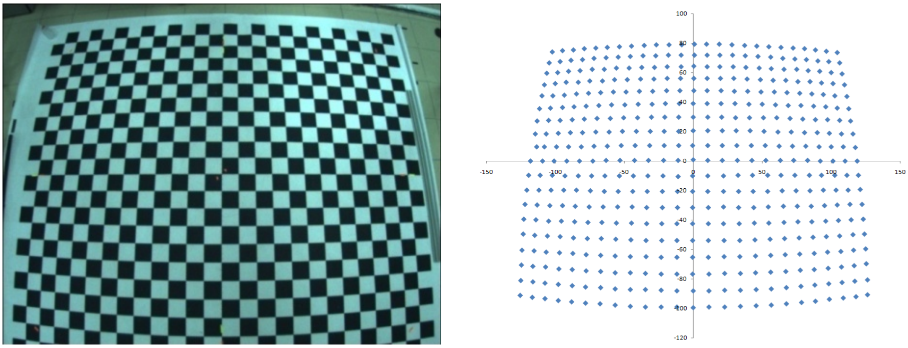


Fig. 4. Sample image and coordinates obtained from a camera height of 200 cm, with lens focal length of 2.8 mm, and camera coordinate position of (3,63)

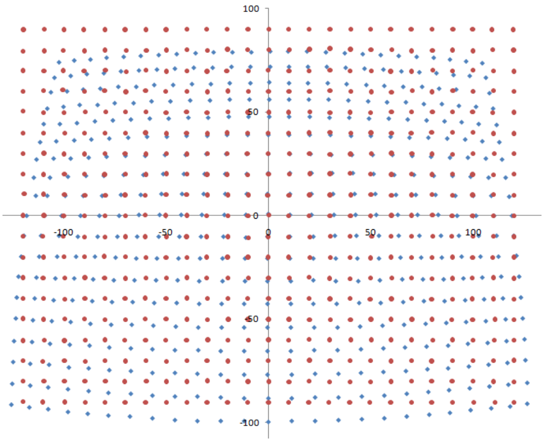


Fig. 5. The result of a coordinate transformation using the ANN method from an image obtained from a camera height of 200 cm, with lens focal length of 2.8 mm, and camera coordinate position (3, 63)

a. Acquisition of the Coordinate References

The coordinate procurement process is conducted by placing a chessboard calibration grid on the field, as shown in Fig 6. The reference coordinates are obtained from the intersecting corners of all the black and white squares. The camera coordinates the acquisition process by setting up the number of the grids to use. In our study, the calibration grid was 21×17 and the sides of all the black and white squares were 10 cm. The next step is to set up the reference coordinates at the upper left corner (X, Y), which in our case was at coordinates (-100, 80). Then, the distance between the vertical and horizontal lines are determined. In our case, that distance was 10, i.e., the distance between the black and white squares in the calibration grid we used was 10 cm.

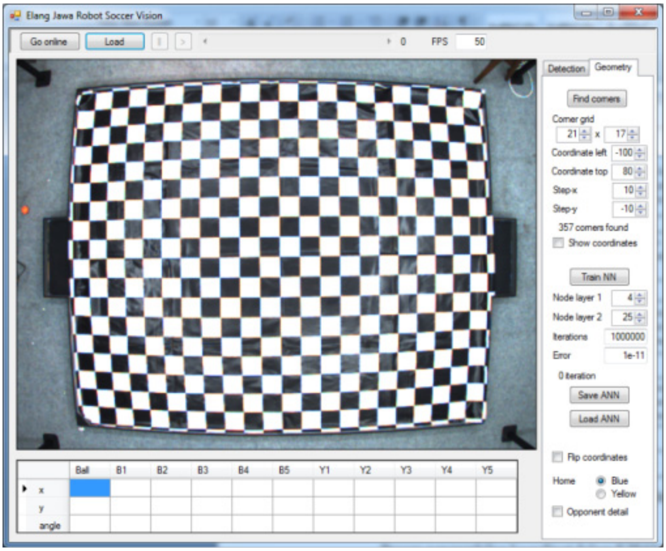


Fig. 6. The image-capturing result using the calibration grid

b. Parameter Preparation for the ANN Learning

To set the parameters for the ANN learning process, the number of hidden nodes in each layer of the ANN model must be determined. In our study, there were four hidden nodes in the first layer and twenty five hidden nodes in the second layer. The maximum number of iterations was set to 10^6 and the minimum error was set to 10^{-12}. A summary of the parameters used in our study are as follows:

- Number of input artificial neural network data = 2
- Output nodes = 2
- Hidden nodes in layer 1 = 4
- Hidden nodes in layer 2 = 25
- Minimum error = 10^{-12}
- Weights initialized using the Nguyen-Widrow method

- Activation function = bipolar sigmoid
- Learning rate = 0.05
- Training method = Levenberg-Marquardt

c. Learning of the ANN model

The learning process was executed to obtain the weight of each node in the hidden layers. The ANN model is a mathematical model of the coordinate transformation process. After the learning is completed, the weight of each node in the hidden layers is obtained.

Coordinate Transformation Process

The coordinate transformation process was implemented by performing calculations on a detected robot with weights derived from the ANN learning. A neural network model from the engine of the robot soccer MiroSot and AndroSot vision systems is shown in Fig. 7. A mathematical model of the coordinate transformation process was derived using the ANN equations 1 and 3.

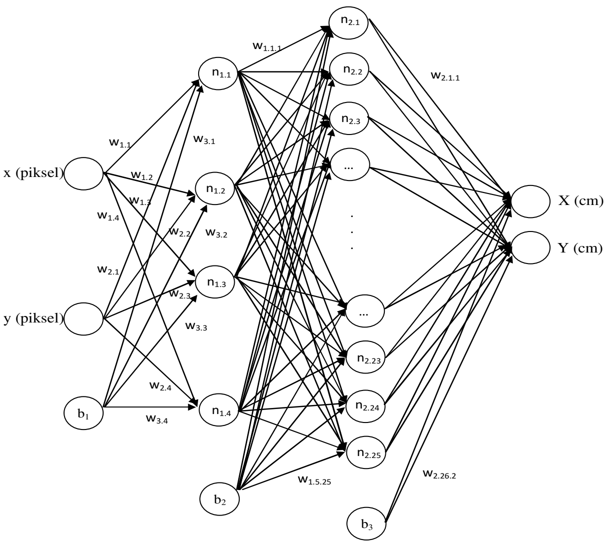


Fig. 7. Development of the ANN model using two inputs and two outputs for the coordinate transformation process from camera coordinates into physical coordinates in the robot soccer MiroSot and AndroSot vision systems

As shown in Fig. 7, the following can be defined:

x and y are the image coordinates
X and Y are the results of the coordinate transformation
$n_{1.k}$ is the node in layer one at line k
$n_{2.j}$ is the node in layer two at line j
f_1 is the transfer function for inputs to layer 1

f_2 is the transfer function for nodes from layer 1 to layer 2
f_3 is the transfer function for nodes from layer 2 to the output
$w_{i.k}$ is the weight of the input node i to the node in layer 1, line k, for $i = 1,2,3$ and $k = 1,2,3,4$
$w_{1.j.k}$ is the weight of the node in layer 1, line k to the node in layer 2, line j, for $k = 1,2,3,4,5$ and $j = 1,2, \dots, 25$
$w_{2.j.l}$ is the weight of the node in layer 2, line j to the output line l, for $j = 1,2, \dots, 26$ and $l = 1,2$
b_1, b_2, and b_3 are the biases of layer 1, layer 2 and layer 3, respectively

The following relations are also true:

$$n_{1.k} = f_1 \left(w_{1.k}x + w_{2.k}y + w_{3.k}b_1 \right), \mathrm{k} = 1, 2, 3, 4 \tag{1}$$

$$n_{2.j} = f_2 \left(\textstyle\sum_{k=1}^{4} w_{2.k.j} n_{1.k} + w_{1.5.j} b_2 \right), \mathrm{j} = 1, 2, \dots, 25 \tag{2}$$

and the following can be derived:

$$X = f_3 \left(\textstyle\sum_{j=1}^{25} w_{2.j.1} n_{2.j} + w_{2.26.1} b_3 \right) \tag{3}$$

$$X = f_3 \left(\textstyle\sum_{j=1}^{25} w_{2.j.1}\, f_2 \left(\sum_{k=1}^{4} w_{1.k.j}\ f_1 \left(w_{1.k}x + w_{2.k}y + w_{3.k}b_1 \right) + w_{1.5.j} b_2 \right) + w_{2.26.1} b_3 \right) \tag{4}$$

$$Y = f_3 \left(\textstyle\sum_{j=1}^{25} w_{2.j.2} n_{2.j} + w_{2.26.2} b_3 \right) \tag{5}$$

$$Y = f_3 \left(\textstyle\sum_{j=1}^{25} w_{2.j.2}\, f_2 \left(\sum_{k=1}^{4} w_{1.k.j}\ f_1 \left(w_{1.k}x + w_{2.k}y + w_{3.k}b_1 \right) + w_{1.5.j} b_2 \right) + w_{2.26.2} b_3 \right) \tag{6}$$

4.3 Experiments and Discussion of the Results of the Camera Calibration Method Based on the Current Camera State-of-the-Art

Coordinate transformation is the process of transforming from the camera coordinates into the physical object coordinates. The coordinate transformation process using the ANN method is as described above. The coordinate references necessary to carry out the transformation process are obtained by a chessboard calibration grid. Several tests were conducted to verify the effectiveness of the coordinate transformation process using artificial neural networks. The tests were conducted to compare with the calibration method by Woo and Park [17, 18] and Xiaobo et al. [15]. Woo and Park employed a calibration method with a 2×10×8×2 artificial neural network [17, 18] and Xiaobo et al. used a 2×5×2 artificial neural network [15]. In this study, the camera calibration method was tested using various images obtained with a camera using various heights and lens focal lengths. The results are shown in Table 3.

Differences in the average error in the resulting coordinates from the transformation process using our ANN model, the ANN model from Woo and Park [17,18], and the ANN model used by Xiaobo et al. [15], were tested using the analysis of variance.

Table 3. Average and maximum error of the result of the coordinate transformation process using our ANN method, the Woo and Park method, and the Xiaobo et al. method

		Our method (ΔX, ΔY)		Woo and Park(ΔX, ΔY)		Xiaobo et al. (ΔX, ΔY)	
		X Axis	Y Axis	X Axis	Y Axis	X Axis	Y Axis
Exp 1	Average	0.1559	0.1651	0.2977	0.3442	1.9047	1.5929
	Maximum	0.8580	1.1270	2.2580	1.9540	7.7300	6.4540
Exp 2	Average	0.2183	0.1552	0.5276	0.3438	1.8448	1.5069
	Maximum	1.0300	0.7390	2.7370	1.6690	7.0600	6.2790
Exp 3	Average	0.1681	0.1680	0.3390	0.1937	1.8614	0.9718
	Maximum	0.7000	1.8080	2.4150	1.3700	7.7800	3.9830
Exp 4	Average	0.0640	0.0676	0.0882	0.0808	1.3321	1.4196
	Maximum	0.3172	0.2896	0.4297	0.3733	7.4602	4.5135
Exp 5	Average	0.1052	0.0780	0.6022	0.2635	1.1559	0.8651
	Maximum	0.4786	0.3983	1.9291	1.2643	7.2643	4.8080
Exp 6	Average	0.2534	0.2153	0.3502	0.2340	1.2183	0.9552
	Maximum	1.3925	1.0076	1.3727	1.1431	7.1431	3.2896
Exp 7	Average	0.2320	0.1979	0.3181	0.2174	1.1681	0.7680
	Maximum	1.1555	0.9486	1.3822	1.3641	5.3641	4.3983
Exp 8	Average	0.2860	0.2468	0.3247	0.1905	1.0640	0.8676
	Maximum	1.0310	0.8043	1.2268	0.9408	6.5276	5.0076
Exp 9	Average	0.2210	0.2124	0.2471	0.1875	1.1052	0.9780
	Maximum	0.9972	1.2560	1.2229	1.0975	7.3390	3.9486
Exp	Average	0.2407	0.1902	0.2435	0.2415	1.2534	0.2153
	Maximum	0.9631	0.7197	1.0636	1.2716	6.0882	4.8043
Exp	Average	0.2518	0.1923	0.3689	0.3711	0.9705	1.1979
	Maximum	0.9532	0.9612	1.6132	1.6195	6.6022	5.2534
Exp	Average	0.2093	0.1914	0.3592	0.2284	0.8292	1.2284
	Maximum	0.8326	0.8117	1.2428	0.9705	7.3502	4.2320
Exp	Average	0.2274	0.2342	0.3899	0.2981	0.8649	1.2981
	Maximum	0.9537	0.7374	1.4425	1.8292	6.3899	4.2860
Exp	Average	0.2586	0.2433	0.3110	0.2274	1.0160	1.2274
	Maximum	1.0094	1.2998	1.3066	0.8649	7.3110	3.2210
Exp	Average	0.2834	0.2097	0.2972	0.2926	1.1427	1.2926
	Maximum	1.2356	1.0801	0.9645	1.0160	7.2972	3.2407
Exp	Average	0.2741	0.2509	0.4864	0.2340	1.4450	1.3983
	Maximum	1.5785	0.8800	1.6064	1.1427	5.4864	3.2518
Exp	Average	0.2965	0.3555	0.3169	0.3699	1.1875	1.0076
	Maximum	1.1697	1.1895	1.1665	1.4450	6.3169	5.2093
Exp	Average	0.3074	0.2397	0.2965	0.3555	1.2415	0.9486
	Maximum	1.1558	1.1118	1.1697	1.1895	7.2965	4.2274
Exp	Average	0.3510	0.1868	0.3960	0.4413	1.3711	1.2860
	Maximum	1.2633	0.6934	1.7337	1.5752	7.3960	3.2860
Exp	Average	0.2807	0.2121	0.4053	0.3096	1.2153	1.2210
	Maximum	1.6548	0.7672	2.1121	1.8687	4.4053	4.2210

Notes: Exp is Experiment; our ANN model is $2 \times 4 \times 25 \times 2$; the Woo and Park model [18,19] is $2 \times 10 \times 8 \times 2$; and the Xiaobo et al. [15] model is $2 \times 5 \times 2$.

Descriptives

PURATA

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
1	20	.217430	.0611557	.0136748	.188808	.246052	.0658	.3260
2	20	.309760	.0816368	.0182545	.271553	.347967	.0845	.4357
3	20	1.185948	.2461822	.0550480	1.070731	1.301164	.7343	1.7488
Total	60	.571046	.4653696	.0600790	.450828	.691264	.0658	1.7488

Test of Homogeneity of Variances

PURATA

Levene Statistic	df1	df2	Sig.
14.816	2	57	.000

Multiple Comparisons

Dependent Variable: PURATA

	(I) MODEL	(J) MODEL	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Dunnett T3	1	2	-.092330*	.0228085	.001	-.149389	-.035271
		3	-.968517*	.0567211	.000	-1.114881	-.822154
	2	1	.092330*	.0228085	.001	.035271	.149389
		3	-.876187*	.0579958	.000	-1.024925	-.727450
	3	1	.968517*	.0567211	.000	.822154	1.114881
		2	.876187*	.0579958	.000	.727450	1.024925
Games-Howell	1	2	-.092330*	.0228085	.001	-.148134	-.036526
		3	-.968517*	.0567211	.000	-1.111320	-.825715
	2	1	.092330*	.0228085	.001	.036526	.148134
		3	-.876187*	.0579958	.000	-1.021374	-.731001
	3	1	.968517*	.0567211	.000	.825715	1.111320
		2	.876187*	.0579958	.000	.731001	1.021374

*. The mean difference is significant at the .05 level.

Fig. 8. Results of the comparison of the average error differences between our ANN model with current ANN models using post-hoc Dunnet's T3 and Games-Howell for SPSS

With respect to the SPSS output terms, homogeneity of variance was not found (P-value >0.05, where the P-value is the probability value). Therefore, the post-hoc analysis method with the assumption of non-homogeneous variance was used. Examination using post-hoc Dunnet's T3 and Games-Howell showed that the results of the analysis are significant in both tests (P-value <0.05), and therefore it was concluded that there is a significant distinction between the average errors for all three methods. Based on the minimum error values obtained, it was concluded that our method is the best, followed by the ANN model by Woo and Park [17, 18], and then the ANN model by Xiaobo et al. [15]. The SPSS analysis results are shown in Fig 8.

5 Conclusions

In our study, coordinate transformation using an artificial neural network method was used to transform the camera pixel coordinates into physical coordinates. Testing and analysis were conducted to verify the effectiveness of the camera calibration method considering many factors, including the camera height, the direction of the camera, the camera rotation, the type of the camera and the lens size. The following conclusions were derived from the overall results of our experiments with the ANN models for the robot soccer MiroSot and AndroSot camera calibration.

The neural network model used in our study, i.e., the 2×4×25×2 model, successfully achieved an objective camera calibration for the robot soccer MiroSot and AndroSot systems. The development of the camera calibration method was done using the architecture and the learning method of the general ANN model to adapt to continuous environmental changes. The relearning method was used to adapt to necessary changes, using new data input for changes in the environments. Relearning was originally implemented to improve performance and efficiency, and to reduce the errors for changing or new complex environments. Relearning on the artificial neural network originally used to adjust the weight was able to be implemented instantly and continuously using new data sets for the new conditions. The accuracy of the experiments using ANN has maximum and average errors that are smaller than those of the ANN model developed by Woo and Park [16, 17, 18] and Xiaobo et al. [15]. This is evidenced by a series of tests conducted using the image database. The maximum errors from the coordinate transformation process using the artificial neural network method based on the current condition are 1.4428 cm. All of the test results from the camera calibration process support the conclusion that the camera calibration method using artificial neural networks is the best solution to resolve the non-linear lens distortion problems, other than the current camera calibration method. The accuracy and efficiency of the camera calibration method using the artificial neural network depends only on the relearning process when the robot environments change.

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