Visual Ball Tracking and Prediction with Unique Segmented Area on Soccer Robot

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***Abstract*-Object detection and tracking system has been developed by several researchers. This paper present algorithm for visual ball detection and ball estimation for goalie (goalkeeper) robot. The ball is captured by a camera with a fish-eye lens and processed for detection and tracking. Images from fish-eye camera are curved images. Images are thresholded to Hue Saturation Value (HSV). The system can predict goal area and ball position with multilayer backpropagation neural network (BPNN). The BPNN inputs are x and y axis of the ball. The BPNN outputs are goal area prediction and ball area prediction. The training data is unique segmented area. According to the changes of previous ball distance, the system will predict the direction of the next ball position. The achievement result (unique kernel 3x3, MSE <0.001, 30 samples data) for ball position prediction is 76.67%. The achievement result (unique kernel 3x3, MSE <0.001, 30 samples data) for goal area prediction is 100%.**

Keywords-HSV, BPNN, goal area prediction, ball position prediction

I. INTRODUCTION

Research in the field of detection and tracking of visual objects has been developed previously. Tran et al [1] created a Pan Tilt Zoom camera system that could detect objects and follow irregular object movements. The object detection system using the threshold in the Hue-Saturation-Value (HSV) color space, then detects the edge of the object by the canny method. Detection of spherical shape is done by hough circle method. The object tracking system is performed by scanning one frame to search for an object moment, specifying object boundaries, and marking objects, determining the midpoint of the object. Sural et al [2] creates an image retrieval with segmentation in the HSV color space, because the Hue index is closer to the perception of human color intensity, thus supporting the classification of objects. Fitriana et al [3] made a study of the segmentation and threshold of the object's color in the HSV space applied to the soccer robot. Ball objects are also detected based on contours, then perform calculations with central moments. The process of morphology of the image that is erosion and dilation done and also apply the method of hough circle to detect the ball in the form of a circle. Hu et al [4] creates an object tracking system by cam-shift method by removing the background element by adding the background material weight busting. The color space used is Hue-Saturation-Intensity (HSI). Hong et al [5] makes about tracking visual objects quickly and effectively with the predicted position of objects on soccer robots. The system created is to detect objects by matching the template with an intersection histogram and a simple linear prediction system that is CLOS or Command Light of Sight, which divides the work area and defines the object's nearest distance with euclidian distance. Zu Jinhui et al [6] created a feature extraction algorithm named biSCAN, an algorithm that can determine the position of the ball and the robot in the field. Scan is done based on the object color and edge detection information of the object. Xiao ming et al [7] created an object tracing system with a multi cues-camshift method. Denis vere et al [10] makes a study of how the movement of a nao robot's head can follow the movement of a spherical object using backpropagation neural network. Paul et al [11] created a control model with neuro controls, so the system can predict and estimate the ball positions.

This research builds the detection system and the prediction system for ball tracking with adjusment parameter of HSV thresholding and process of morphological image (erosion and dilation). The Images captured by fish-eye lens camera. The images are converted from RGB to HSV. The images are done with HSV thresholding and morphological process. The center of ball as input for multilayer backpropagation neural network (multilayer BPNN). The system can predict the goal area and the ball position with multilayer BPNN and applied for goalie wheeled soccer robot as seen in Fig. 1.

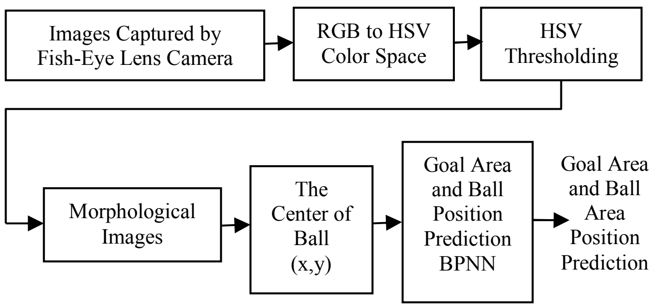


Fig. 1. Diagram of The System Process

II. HUE SATURATION VALUE THRESHOLDING

A. Hue-Saturation-Value (HSV) Color Space

The ball was captured using a fish-eye lens camera. The images dimension are Red Green Blue or RGB color space. The images is change into HSV, as it approaches the natural color like the human eye. Hue represents the type of color can be illustrated in the angle of the circle, the value 0-360 is normalized to 0-255, where 0 is red. Saturation represents the strength of color with the range 0-255, the smaller the more color gray so the color fade. Value represents the brightness level of the color with the range 0-255, where the value 0 is very dark and the 255 value is very bright. This HSV model is close to a human-owned system. The luminance component model (brightness) is composed of color pairs namely hue and saturation [12]. The mathematical modeling equation of the RGB model to the HSV model is in (1),(2),(3), and (4)

$$H = \begin{cases} 60\left(\frac{G-B}{\delta}\right) & if\ MAX = R \\ 60\left(\frac{B-R}{\delta}+2\right) & if\ MAX = G \\ 60\left(\frac{R-G}{\delta}+4\right) & if\ MAX = B \\ not\ defined & if\ MAX = 0 \end{cases} \tag{1}$$

$$S = \begin{cases} 60\left(\frac{\delta}{MAX}\right) & if\ MAX \neq 0 \\ 0 & if\ MAX = 0 \end{cases} \tag{2}$$

$$V = MAX \tag{3}$$

The value δ=MAX-MIN and MAX = max(R,G,B) and MIN = min (R,G,B), Where the RGB value scale is [0,1]; The value of H is limited to the range [0.360].

$$H = H + 360, \quad if\ H < 0 \tag{4}$$

When looking at a color, the system in humans defines the color characteristics based on the brightness and chroma of color or the same we define with Hue and Saturation [8,9].

B. HSV Thresholding

Thresholding is a way to set limits on the color workspace of an image. Determination of color restrictions on the ball image is done by limiting the value of Hue, Saturation, and Value, so as to obtain the optimal combination of image data experiment.

$$\text{Threshold} = \left\{ \begin{array}{l} H_{min} < \text{Hue Bola} < H_{maks} \\ S_{min} < \text{Saturation Bola} < S_{maks} \\ V_{min} < \text{Value Bola} < V_{maks} \end{array} \right\} \tag{5}$$

C. Morphological : Opening and Closing

Morphological is an image enhancement process consisting of a process called opening and closing. Image of threshold result of HSV will be done opening and closing process. 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. The process of Erosion and Dilation is done by multiplying the image with the elemental matrix of structure by working like a convolution. 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. Opening and closing operations such as (6) and (7). This process is used to obtain information integrity due to curved field conditions.

$$A \circ B = (A \ominus B) \oplus B \tag{6}$$

$$A \bullet B = (A \oplus B) \ominus B \tag{7}$$

III. MULTILAYER BACKPROPAGATION NEURAL NETWORK (MULTILAYER BPNN)

The center of ball is determined on screen (x, y). It used for multilayer BPNN training data and multilayer BPNN testing data. The ball move with zero acceleration and constant velocity. The BPNN architecture is consist of two input layer nodes, one hidden layer node, and one output layer node. Three layers are named as input layer X_i, *hidden* layer (O_i^{L1}), and output layer O_i^{L2}. The hidden input layer and layer are connected with the weight $W^{L1-L2}{}_{i,j}$ and between the hidden layer and the output layer connected by the weigher $W^{L2-L3}{}_{i,j}$. The artificial neural network learn with data pair between input data and output data. The temporary output data error was forwarded to the output layer. The output layer provide a response called a temporary output. If the output does not reach the limit of convergence or reach the mean square error limits, it is adjusted the weight on the hidden layer and weight for backwards to the input layer. The algorithm is constructed with the following mathematical equations:

A. Mathematical for Forward Propagation

Layer 1

$$O_i^{L1} = X_i \tag{8}$$

Layer 2

$$a_j = \sum_{i=1}^{N} O_i^{L1} W^{L1-L2}{}_{i,j} \tag{9}$$

and

$$O_i^{L2} = \frac{1}{1+\exp^{-(a_j + bias_j)}} \tag{10}$$

Layer 3

$$b_k = \sum_{j=1}^{N} O_j^{L2} W^{L2-L3}{}_{i,j} \quad (11)$$

and $$O_k^{L3} = \frac{1}{1+\exp^{-(b_k+bias_k)}} \quad (12)$$

B. Mathematical for Backward Propagation

Error Output Layer 3

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

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

Error Output Layer 2

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

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

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

C. Mathematical for Bias

Weight Update L2-L3

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

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

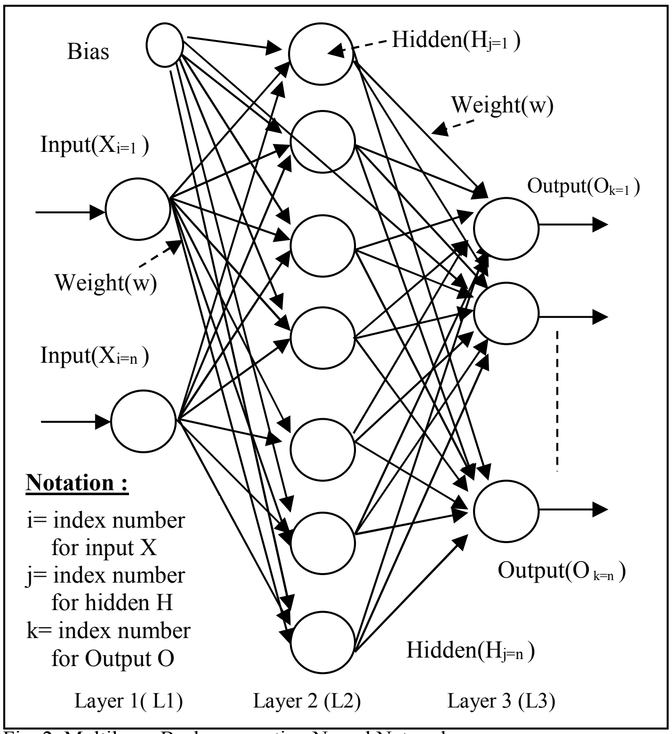


Fig. 2. Multilayer Backpropagation Neural Network

Weight Update L1-L2

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

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

Weight Update for Bias L2-L3

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

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

Weight Update for Bias L1-L2

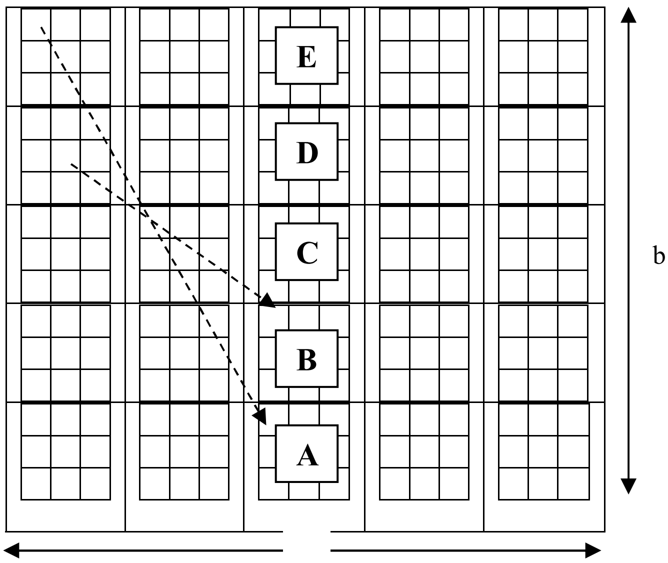
$$\Delta bias_j^{L1-L2} = \eta.\frac{dErr_j}{dbias_j^{L1-L2}} = \eta.\frac{dErr_k}{da_j}.\frac{da_j}{dbias_k^{L1-L2}} = \eta.\partial_2.1 \quad (24)$$

$$bias^{L2-L3} = bias^{L2-L3} + \Delta bias_j^{L2-L3} \quad (25)$$

D. Learning Rate Update

$$Learning\_rate = \mu(k) = \frac{\mu_0}{1+\frac{k}{k_0}} \quad (26)$$

The BPNN architecture as shown in Fig. 2. The BPNN has three layers. There are input layer, hidden layer, and output layer. Input layer design with 2 nodes (Ball position x and Ball position y). Hidden layer design with 10 nodes. Output layer design with 5 nodes. The unique data was generate as shown in Table I. The goal and position status was generate in Table II. The uniquely data is segmented area into 25 main parts, output layer in 5 bit design, with each part done segmentation measuring 3x3 (9 parts) as shown in Fig. 3 and Fig. 4.



a = segmentation of width area;
b= segmentation of height area;
A,B,C,D,E = prediction area;

Fig. 3. Area Segmentation for Position Prediction

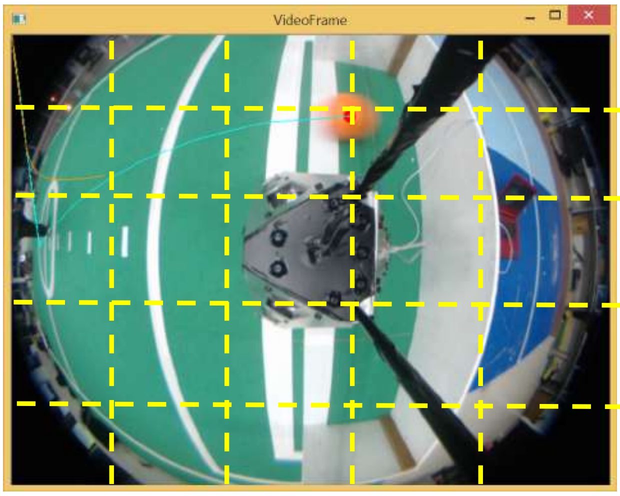


Fig. 4. Segmented Area View From Goalie Robot

The BPNN is using data on Table I and Table II for training. The weight result after training is saved on memory for mapping process.

IV. Experiment

A. Results and Discussion for Thresholding

The system that has been created for visual object detection is by using the conversion from RGB to HSV, then doing the thresholding and morphology of the image. The image size is 640x384. The results can be seen in Fig. 2. The experiment for initial HSV Threshold value are H = 0- 150; S = 157-255; V = 180-255. The experiment for morphological image kernel is ellipse with matrix 5x5. The result for HSV thresholding is ball detected correctly.

B. Results and Discussions for Goal Area and Ball Position Prediction and Position with Multilayer Backpropagation Neural Network

The experiment with BPNN are done with the online camera. Field from the results of fish-eye shaped cameras.

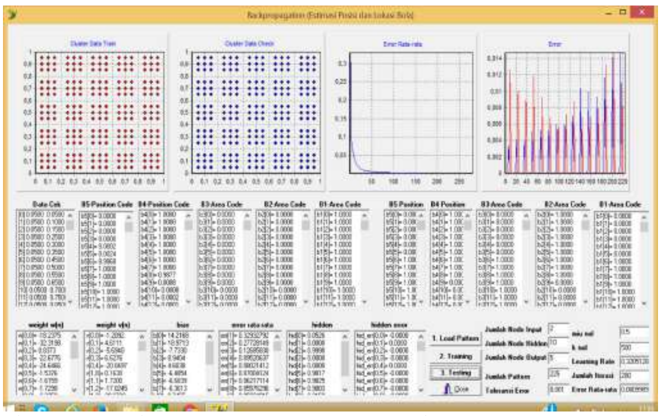


Fig. 5. Experiment BPNN, Layer 1-2 and Layer 2-3, MSE<0.001, convergen at iteration 280

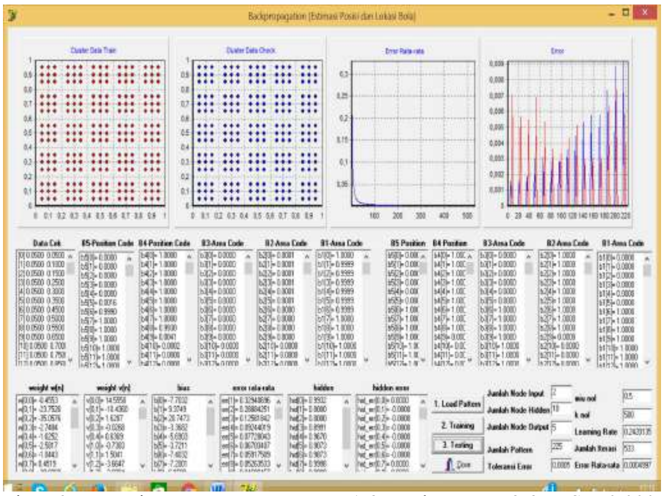


Fig. 6. Experiment BPNN, Layer 1-2 and Layer 2-3, MSE<0.0005, convergen at iteration 530.

The experiment of the ball position are done by kicking a ball towards the robot. The response data of BPNN that trained with unique segmented data as shown on Table III. The experiments are training and testing with Mean Square Error<0.001 and Mean Square Error<0.0005 as seen on Fig. 5 and Fig. 6. The Weights of training are saved in memory. The weights of training are used for forward BPNN process so the prediction of ball positions as done. The results of the research are prediction of the goal area position and ball area position. The unique segmented data and sub segmented data are generated aims to give the ball location for goalie robot.

Fig. 7. Real Time Results Ball Position against Goal

```
int BPNN_mapping()
{for (p = 0; p < jml_pattern; p = p + 1) {
 for (i = 0; i < jml_hidden; i = i + 1) {
 tmp_hidden1 = 0;
 for (j = 0; j < jml_input; j = j + 1) {
     tmp_hidden1+=y_inp[p][j] * w[j][i];}
     hidden[i] = (1 / (1 + exp(-1.0*(tmp_hidden1+bias[i]))));}
     for (i = 0; i < jml_output; i = i + 1) {
               tmp_hidden2 = 0;
               for (j = 0; j < jml_hidden; j = j + 1) {
               tmp_hidden2+= hidden[j] * v[j][i];}
y_out[p][i] = (1/(1 + exp(-1.0*(tmp_hidden2+bias[i+jml_hidden]))));}}
return 0;
}
```

Fig. 8. Multilayer BPNN with VC++ Comunity 2017

TABLE I. UNIQUE TRAINING DATA FOR SEGMENT AND SUB SEGMENT AREA, KERNEL 3x3

	1						2						3						4						5					
	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y	x	y
	0.05	0.05	0.10	0.05	0.15	0.05	0.25	0.05	0.3	0.05	0.35	0.05	0.45	0.05	0.5	0.05	0.55	0.05	0.65	0.05	0.7	0.05	0.75	0.05	0.85	0.05	0.9	0.05	0.95	0.05
1	0.05	0.10	0.10	0.10	0.15	0.10	0.25	0.10	0.3	0.10	0.35	0.10	0.45	0.10	0.5	0.10	0.55	0.10	0.65	0.10	0.7	0.10	0.75	0.10	0.85	0.10	0.9	0.10	0.95	0.10
	0.05	0.15	0.10	0.15	0.15	0.15	0.25	0.15	0.3	0.15	0.35	0.15	0.45	0.15	0.5	0.15	0.55	0.15	0.65	0.15	0.7	0.15	0.75	0.15	0.85	0.15	0.9	0.15	0.95	0.15
	0.05	0.25	0.10	0.25	0.15	0.25	0.25	0.25	0.3	0.25	0.35	0.25	0.45	0.25	0.5	0.25	0.55	0.25	0.65	0.25	0.7	0.25	0.75	0.25	0.85	0.25	0.9	0.25	0.95	0.25
2	0.05	0.30	0.10	0.30	0.15	0.30	0.25	0.30	0.3	0.30	0.35	0.30	0.45	0.30	0.5	0.30	0.55	0.30	0.65	0.30	0.7	0.30	0.75	0.30	0.85	0.30	0.9	0.30	0.95	0.30
	0.05	0.35	0.10	0.35	0.15	0.35	0.25	0.35	0.3	0.35	0.35	0.35	0.45	0.35	0.5	0.35	0.55	0.35	0.65	0.35	0.7	0.35	0.75	0.35	0.85	0.35	0.9	0.35	0.95	0.35
	0.05	0.45	0.10	0.45	0.15	0.45	0.25	0.45	0.3	0.45	0.35	0.45	0.45	0.45	0.5	0.45	0.55	0.45	0.65	0.45	0.7	0.45	0.75	0.45	0.85	0.45	0.9	0.45	0.95	0.45
3	0.05	0.50	0.10	0.50	0.15	0.50	0.25	0.50	0.3	0.50	0.35	0.50	0.45	0.50	0.5	0.50	0.55	0.50	0.65	0.50	0.7	0.50	0.75	0.50	0.85	0.50	0.9	0.50	0.95	0.50
	0.05	0.55	0.10	0.55	0.15	0.55	0.25	0.55	0.3	0.55	0.35	0.55	0.45	0.55	0.5	0.55	0.55	0.55	0.65	0.55	0.7	0.55	0.75	0.55	0.85	0.55	0.9	0.55	0.95	0.55
	0.05	0.65	0.10	0.65	0.15	0.65	0.25	0.65	0.3	0.65	0.35	0.65	0.45	0.65	0.5	0.65	0.55	0.65	0.65	0.65	0.7	0.65	0.75	0.65	0.85	0.65	0.9	0.65	0.95	0.65
4	0.05	0.70	0.10	0.70	0.15	0.70	0.25	0.70	0.3	0.70	0.35	0.70	0.45	0.70	0.5	0.70	0.55	0.70	0.65	0.70	0.7	0.70	0.75	0.70	0.85	0.70	0.9	0.70	0.95	0.70
	0.05	0.75	0.10	0.75	0.15	0.75	0.25	0.75	0.3	0.75	0.35	0.75	0.45	0.75	0.5	0.75	0.55	0.75	0.65	0.75	0.7	0.75	0.75	0.75	0.85	0.75	0.9	0.75	0.95	0.75
	0.05	0.85	0.10	0.85	0.15	0.85	0.25	0.85	0.3	0.85	0.35	0.85	0.45	0.85	0.5	0.85	0.55	0.85	0.65	0.85	0.7	0.85	0.75	0.85	0.85	0.85	0.9	0.85	0.95	0.85
5	0.05	0.90	0.10	0.90	0.15	0.90	0.25	0.90	0.3	0.90	0.35	0.90	0.45	0.90	0.5	0.90	0.55	0.90	0.65	0.90	0.7	0.90	0.75	0.90	0.85	0.90	0.9	0.90	0.95	0.90
	0.05	0.95	0.10	0.95	0.15	0.95	0.25	0.95	0.3	0.95	0.35	0.95	0.45	0.95	0.5	0.95	0.55	0.95	0.65	0.95	0.7	0.95	0.75	0.95	0.85	0.95	0.9	0.95	0.95	0.95

TABLE II. SAMPLE OF SUB-SEGMENT 5 BIT UNIQUE CODE FOR POSITION (LEFT, CENTER, LEFT) AND AREA CODE (1,2,3,4, AND 5)

Position		Position Code (2 MSB Bit) 01 = LEFT(L) ; 11 = Center(C); 10 = RIGHT(R)		Area Code (1=001;2=010;3=011;4=100;5101)		
X	Y	bit 5	bit 4	bit 3	bit 2	bit 1
0.05	0.05	0	1	0	0	1
0.05	0.10	0	1	0	0	1
0.05	0.15	0	1	0	0	1
0.05	0.25	0	1	0	0	1
0.05	0.30	0	1	0	0	1
0.05	0.35	0	1	0	0	1
0.05	0.45	1	1	0	0	1
0.05	0.50	1	1	0	0	1
0.05	0.55	1	1	0	0	1
0.05	0.65	1	0	0	0	1
0.05	0.70	1	0	0	0	1
0.05	0.75	1	0	0	0	1
0.05	0.85	1	0	0	0	1
0.05	0.90	1	0	0	0	1
0.05	0.95	1	0	0	0	1

Note : bit 5 and bit 4 : Position of the ball to the robot (left, center, right)
bit 3, bit 2, dan bit 1 : Area of the ball (ball position prediction) for soccer goalie robot.

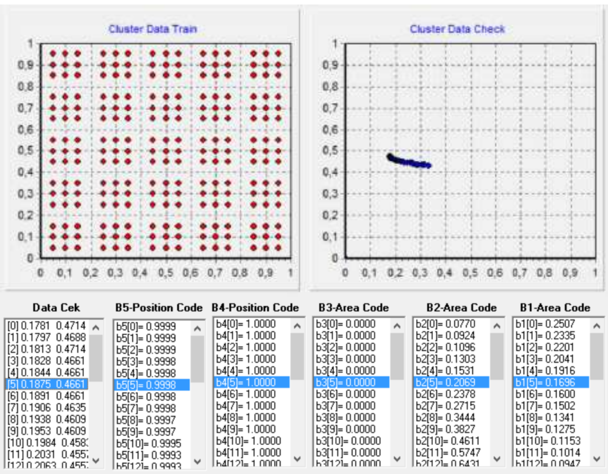


Fig. 9. Result for Goal Prediction and Position Prediction

The mapping of BPNN source code for this simulation is shown in Fig. 8. The simulation graphics for mapping is shown in Fig. 9.

The experimental technique is record ball movement for the center and half of the field are to the robot. The reference condition is shown on Table II. The ball position reference is recognized in center position form the robot. The goal position prediction is in center area (C). The ball simulation is moving from area 1 (code 0 0 1) to area 2 (0 1 0).

The experimental result for 30 data as shown in Fig. 10 and Table III. The achievement result (30 samples data) for goal area prediction is 100%. The achievement result (30 samples data) for ball position prediction is 76.67%. The errors caused by the minimized of area data training. The unique data can be extended from unique kernel area 3x3 to unique kernel area 5x5 or unique kernel area 7x7.

TABLE III. RESULT WITH UNIQUE KERNEL AREA 3x3

time-	Real Data		Unique Range		Ref Area		Actual Area		Error	Error Ball
	X	Y	X	Y	Goal	Position	Goal	Position	Goal	Position
1	114	181	0.178125	0.471354	C	1	C	1	No	No
2	115	180	0.179688	0.468750	C	1	C	1	No	No
3	116	181	0.181250	0.471354	C	1	C	1	No	No
4	117	179	0.182813	0.466146	C	1	C	1	No	No
5	118	179	0.184375	0.466146	C	1	C	1	No	No
6	120	179	0.187500	0.466146	C	1	C	1	No	No
7	121	179	0.189063	0.466146	C	1	C	1	No	No
8	122	178	0.190625	0.463542	C	1	C	1	No	No
9	124	177	0.193750	0.460938	C	1	C	1	No	No
10	125	177	0.195313	0.460938	C	1	C	1	No	No
11	127	176	0.198438	0.458333	C	1	C	2	No	Error
12	130	175	0.203125	0.455729	C	1	C	2	No	Error
13	132	175	0.206250	0.455729	C	1	C	2	No	Error
14	134	174	0.209375	0.453125	C	1	C	2	No	Error
15	136	174	0.212500	0.453125	C	1	C	2	No	Error
16	138	174	0.215625	0.453125	C	2	C	2	No	No
17	142	173	0.221875	0.450521	C	2	C	2	No	No
18	144	173	0.225000	0.450521	C	2	C	2	No	No
19	148	172	0.231250	0.447917	C	2	C	2	No	No
20	151	171	0.235938	0.445313	C	2	C	2	No	No
21	157	170	0.245313	0.442708	C	2	C	2	No	No
22	159	170	0.248438	0.442708	C	2	C	2	No	No
23	166	170	0.259375	0.442708	C	2	C	2	No	No
24	170	170	0.265625	0.442708	C	2	C	2	No	No
25	174	169	0.271875	0.440104	C	2	C	2	No	No
26	182	168	0.284375	0.437500	C	2	C	2	No	No
27	187	168	0.292188	0.437500	C	2	C	2	No	No
28	197	168	0.307813	0.437500	C	2	C	2	No	No
29	203	167	0.317188	0.434896	C	2	C	3	No	Error
30	214	166	0.334375	0.432292	C	2	C	3	No	Error
Error(%)									0%	23.33%

V. CONCLUSION AND FUTURE WORK

Visual object detection (ball detection) system can work well, the achievement result (unique kernel 3x3, MSE <0.001, 30 samples data) for ball position prediction is 76.67% and the achievement result (unique kernel 3x3, MSE <0.001, 30 samples data) for goal area prediction is 100%. The system can predict the goal area and ball position. The future work for the robots are given the ability to predict position and speed (velocity) of the ball also the ability to block the ball. The future work for the system is larger kernel data more than 3x3 and applied to the real robot.

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