Malaysian Journal of Computer Science, Vol. 15 No. 1, June 2002, pp. 57-67

AUTOMATIC CLASSIFICATION OF OFFENSIVE PATTERNS FOR SOCCER GAME HIGHLIGHTS USING NEURAL NETWORKS

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ABSTRACT

A method for the automatic classification of offensive patterns in soccer games has been developed using neural networks technique. Back-propagation (BP) neural network techniques have been applied to obtain data that define the positions of both a player and the ball on the ground. The offensive patterns have been formulated from the group formations and enable automatic indexing of the highlights of soccer games. Excepts from actual soccer games including some from the 1998 French World Cup yielded 297 video clips which were categorized into the following five types of pattern: Left-Running are 60, Right-Running 74, Center-Running 72, Corner-Kick 39 and Free-Kick 52. Examination of the results shows the following rates of satisfactory pattern recognition: Left-Running comes to 91.7%, Right-Running 100%, Center-Running 87.5%, Corner-Kick 97.4% and Free-Kick 75%.

Keywords: ***Soccer game; Offensive pattern; Neural network; Back-propagation (BP) group formations***

1.0 INTRODUCTION

The technique of image processing has been expanding beyond such conventional applications as human body facial or gesture recognition to the sports field [1]. Increased interest in soccer generated by the up-coming 2002 World Cup Games in Korea and Japan has caused the study of soccer game analysis. The isolation and tracking of moving players moving from an input image are rather complex problems that the computer is required to solve [1-4]. The automatic extraction of soccer highlights for TV broadcast must include the most intense action and important plays of the game in order to effectively compress the whole soccer game into a short period of time [4]. Broadcast of the highlights will remove the more boring parts of a game and make it possible for viewers to watch only the significant plays and action. Moreover, compared to the length of an entire soccer game, the highlights are of relatively short duration and are rarely repeated in any particular game. In addition, analysis of the highlights can give team players and staff including the manager or coach access to high-level scientific information. This will permit the development of more advanced playing techniques and the building of more effective strategies for the game. Such analysis could form the basis for the effective use by an athletic team of a video library of specific games [4].

Many studies related to group behaviour or teamwork as a basis for the automatic indexing of soccer highlights have been reported [1-9]. Most of these, however, are limited to motion recognition of an individual player and few of them take into account effects of teamwork or group behaviour and only a small number are based on the technique of offensive pattern recognition. Compared to individual player movement recognition, the recognition of group behaviour or the classification of an offensive pattern is a far more difficult task because it must reflect not only the individual player’s action but the position of the group's position as well [1, 10].

Research on soccer game analysis has been done at the Pohang University of Science and Technology [11-13]. Their studies focused on tracking the ball and the movement recognition of an individual player using color histogram techniques that cannot be applied to highlight indexing.

There have been some other studies on the recognition of group behaviour as well as the actions of individual players but they too, are limited to analysing the actions of individual players. A group at MIT analysed the group behaviour exhibited in American football game [14 -15], and there have been some other studies including Collins [6], Bobick [7], Gong et al. [8], Yoshida and Ozawa [9] and Iwase et al. [10].

Their studies were restricted to the recognition of an individual player and to two-dimensional images rather than the recognition of group formations based on mutually inter-related movement. The same image seen from different angles might be incorrectly recognised if the background were changed and no solution has been found to identify and correct this problem.

For tracking the positions of a player and ball, research based on feature point by color based technique [17-20] in which input images are transformed into field models and correspond to the positions in an actual field, is also of interest to many researchers.

In this paper, we propose a method for classifying soccer game offensive patterns using the automatic extraction of soccer game highlights employing the neural networks technique. It is based on group formations produced by qualitative analysis of partial relationships in time and space. The first important component of our system is the automatic detection of the player, the ball and some field lines by means of image processing.

2.0 CLASSIFICATION OF OFFENSIVE PATTERNS USING NEURAL NETWORKS

2.1 Basic Tactics and Strategies in Soccer Games

The formation is to observe various movements toward the goal of each team. Furthermore, recognising and classifying offensive patterns during formation is an essential factor for automatically indexing soccer highlights. Widely used offensive tactics as of now are 4-2-4, 4-3-3, 4-4-2, 3-5-2, and 3-4-3.

The tactics in soccer games involve the positions and activities of players. Various tactics are shown in Table 1 and the tactics may be selected with the characteristics of each team. The following details on explanations of tactics involving many players.

Table 1: History of tactics in soccer games

Tactics/Contents Year	Tactics	Contents
1863 □1900	1-1-8 1-2-7	Assigned many players to Forward.
1900's	2-2-6 2-3-5	Allotment of defending players come to be important because of development of past technique.
1925□958	3-2-2-3	Three full back system comes into fashion.
After 1958	4-2-4	Brazilian team in the World Cup attracted public attention by using this system.
1960's	4-3-4 1-4-2-3 1-4-3-2	Three Tactics described on the left were in fashion, and 1-4-2-3 and 1-4-3-2 were allotted a sweeper.
1970's	4-4-2	This offence has been used till now.
1980 □1990	3-5-2 3-4-3	This offences are still employed today.

Fig. 1 and Fig. 2 show examples of 3-4-3 tactics used by the Paraguayan team, who beat Barcelona in 1992, and 3-5-2 by the Spanish team in the Olympic soccer final of Barcelona in 1992.

If we check the position and function of players in Fig. 1 and Fig. 2, the difference of tactics between the two teams is that only one player is allotted the half position of defence on the Spanish team but two players fulfill this role for the Paraguayan team. The half line of the Spanish player is positioned. No. 9 is positioned below both No. 7 and No. 8, above on both sides. On the Paraguayan side, however, both No. 7 and No. 8 are positioned above of each side, and No. 9 is above the real center to play a role as a center forward. To automatically index the highlights of a soccer game, the analysis of group formations is required, and we propose an automatic classification technique of offence patterns as groundwork for this task ahead.

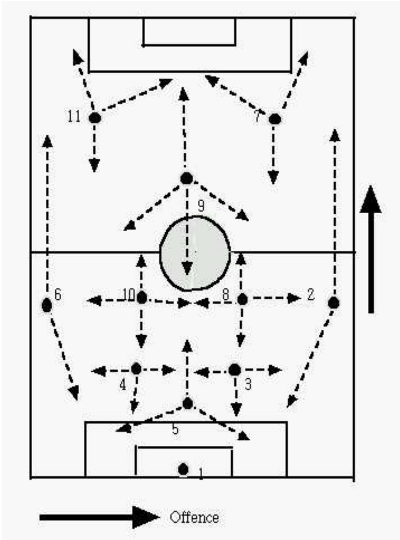


Fig. 1: Formation of 3-4-3 tactic in Paraguayan Team

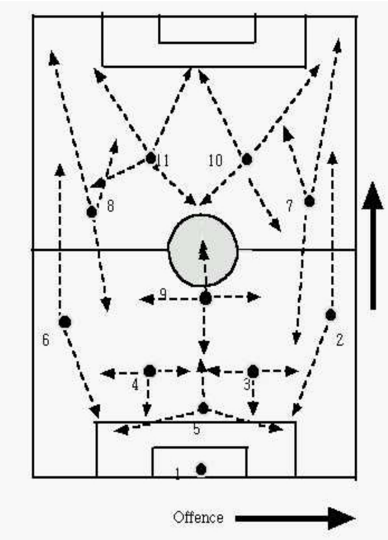


Fig. 2: Formation of 3-5-2 tactic in Spanish team

2.2 Classification of Offensive Patterns Using Neural Networks

It is important to determine the coordinates of a ball and the player, and to determine their patterns by automatically segmenting scenes from video image sequences, and receiving ground field situations and the position relationships between the ball and objects as entry information from segmented scenes. By image classification of soccer video, all related objects are clustered, and on the basis of the contents of the offensive pattern by the formation, they can be automatically classified. While clustering the coordinates of a player and the ball, the distance between a player and the ball are calculated, and the player who is the closest to the ball is regarded as having the ball and given weight.

The data presented here is a representative frame from scenes of video sequences and the frame is used as entry information. Although the offensive patterns of a soccer game differ, we can classify the next five patterns when we consider the position of the players and the ball.

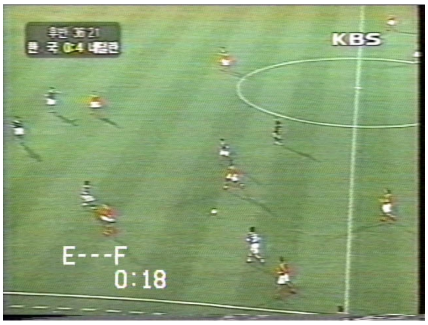
(i) Left-Running: The ball goes to the left and the movement (energy) of the players gathered around the left; that is, the energy density is high on the left.

(ii) Right Running: The ball goes to the right, and the movement (energy) of the players is gathered around the right; that is, the energy density is high on the right.

(iii) Center-Running: The ball goes toward the center and the movement (energy) of the players is gathered around center; that is, energy density is high in the center.

(iv) Corner-Kick: The ball is on the corner and a wall is formed by players in front of the goal posts and is distributed laterally; that is, high density energy is extended laterally.

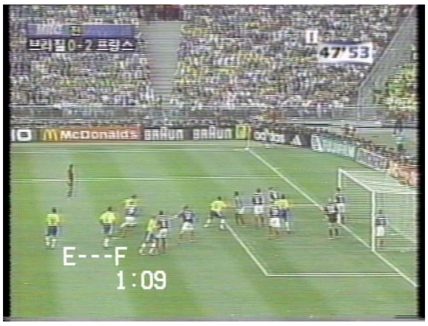
(v) Free-Kick: A wall of offensive players is formed in front of the ball and a wall of the opponent's players in front of the goal posts. The following pictures show offensive patterns as defined in Fig. 3, extracted from Korea versus Netherlands and Brazil versus prance game.



(a) Left-Running of Korea team

(b) Right-Running of Korea team

(c) Center-Running of Korea team



(d) Corner-Kick of Brazil team

(e) Free-Kick of Brazil team

Fig. 3: The examples of offensive patterns extracted from Korea versus Netherlands and Brazil versus prance game

3.0 STRUCTURE OF NEURAL NETWORKS TO RECOGNITION AND CLASSIFY OFFENSIVE PATTERNS

3.1 Steps for Classification of Offensive Patterns

In this work, we apply a BP algorithm among a neural nets technique with a three-layered structure. Even in the same left or right offensive patterns, the positions of players can be different according to the point of view. By learning such situations using the BP algorithm, our method could recognise the patterns optimally. Networks were designed such that the number of neurons of the input layer was $12 \times 9 = 108$, the number of neurons of the hidden layer was 11, corresponding to about a tenth of the number of input layers, and that of the output layer to 5 as the kinds of recognised patterns are five, based on a FIFA regulation 120×90 meter soccer-field (Fig. 4).

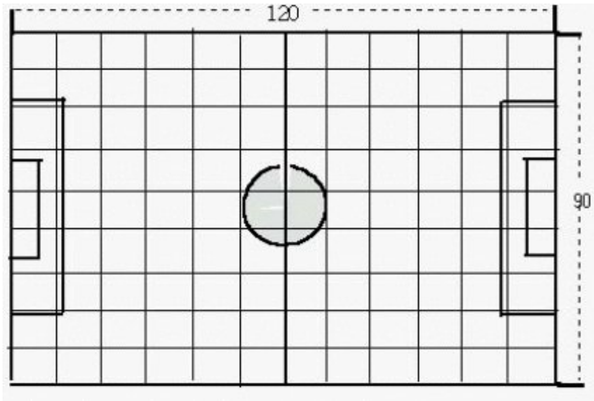


Fig. 4: Mesh features for BP neural net from soccer ground

The process of movement analysis algorithm of group formation is as follows:

Step 1: Initialise weight W_{ji}, W_{kj} deciding network situation and offsets θ_j, θ_k to smallest random number between -0.5 and 0.5, respectively.

Step 2: Establish pattern of learning

(i) Compute input net_{pj} of hidden layer unit j using output value O_{pj} i suggested from input layer unit with learning pattern value, weight W_{ji} between input and hidden layers and offsets θ_j of hidden layer unit j.

$$net_{pj} = \sum_i W_{ji} O_{pi} + \theta_j . \quad (7)$$

(ii) Calculate output O_{pi} of hidden layer unit j from net_{pj} and f of sigmoid function.

$$O_{pj} = f_j (net_{pj}). \quad (8)$$

(iii) Compute input net_{pk} of output layer unit k from output O_{pj} of hidden layer unit, weight W_{kj} between hidden and output layers and offsets θ_k of output layer unit k.

$$net_{pk} = \sum_j W_{kj} O_{pj} + \theta_k . \quad (9)$$

(iv) Compute output O_{pk} of output layer unit k from net_{pk} and sigmoid function, f.

$$O_{pk} = f_k (net_{pk}). \quad (10)$$

(v) Compute an error δ_{pk} to weight and offsets of output layer unit k from the difference between object output t_{pk} of learning pattern and actual output O_{pk}.

$$\delta_{pk} = (t_{pk} - O_{pk}) f_k (net_{pk}) = (t_{pk} - O_{pk}) O_{pk} (1 - O_{pk}). \quad (11)$$

(vi) Compute an error δ_{pj} to weight and offsets of hidden layer unit j from error δ_{pk}, weight W_{kj} between hidden and output layers and output net_{pj} of hidden layer.

$$\delta_{pj} = f_j (net_{pj}) \sum_k \delta_{pk} W_{kj} = \sum_k \delta_{pk} W_{kj} O_{pj} (1 - O_{pj}). \quad (12)$$

Step 3: Modify weight and offsets

(i) Modify weight W_{kj} connected hidden layer unit j and output layer unit k by adding the multiplex of error δ_{pk} from output layer unit k in step 5 , output O_{pj} of hidden layer unit j and integer number α.

$$W_{kj} = W_{kj} + \alpha \cdot \delta_{pk} O_{pj} . \quad (13)$$

(ii) Modify offsets θ_k of output layer unit k by adding the multiplex of error δ_{pk} and integer number β.

$$\theta_k = \theta_k + \beta \cdot \delta_{pk} \,. \tag{14}$$

Step 4: Alter weights and revise offsets

(i) Alter weights W_{ji} connected to unit j of input layer and hidden layer by adding multiplex of error δ_{pj} of hidden layer unit j, output O_{pj} of input layer unit i and integer number α.

$$W_{ji} = W_{ji} + \alpha \cdot \delta_{pj} \; O_{pi} \,. \tag{15}$$

(ii) Revise offsets θ_j of hidden layer unit j by adding the multiplex of error δ_{pj} and integer number β.

$$\theta_j = \theta_j + \beta \cdot \delta_{pj} \,. \tag{16}$$

Step 5: Terminate if learning pattern is ended, or go to step 2 to repeat it.

3.2 Generation of BP Neural Networks

(1) Encoding method of input, hidden and output neurons of neural networks

The layout of the neurons with three-layer are 108 for the input layer. Here, the number of neurons of the input layer is decided by the size of the field model. That of the hidden layer is assigned the value of eleven acquired from the heuristic experiments, and it corresponds to around one-tenth of the neuron numbers of the input layer. Since there are five number patterns to recognise, the number of the neurons of the output layer is also set to five. Each of the five neurons plays a role in recognising and expressing the five Offensive patterns, Left, Right, Center Running, Corner, and Free Kick.

On the basis of the above circumstances, the position vector values of a player and the ball expressed in the field models are given the most suitable values from the heuristic experiments. That is, a ball is 1.0, a player with a ball is 0.5, and 0.5 is added to the position vectors. The values acquired by the allocation method of weight are normalised to be between 0 and 1 to use as data for further experiments.

Next, we set the learning data of four Offensive patterns (Left, Right, Center attack and Free-Kick), excluding Corner-Kick, to twenty each, and learning data to forty since representative patterns can appear in each of the four corners of the field. The total sum of learning data was one hundred and twenty (20+20+20+40+20) and the patterns of recognition are the output value with the largest value of recognition among the five patterns. Values with 0.1 and less are regarded as no recognition.

As experimental data, we analysed a total of 297 recognition patterns that were used to distinguish team to team: Left-Running are 30 pairs (60), Right-Running 37(74), Center-Running 36(72), Corner-Kick 19.5(39), and Free-Kick 26(52).

We also fixed the error tolerance δ_{pj} at 0.001(mean error of one pattern per cycle), the learning constant at 0.001, the factor value to speed up learning (momentum: a factor for advancing learning speed) at 0.001, the factor value of out of error δ_{pk} (a range out of local minimum value) at 0.001, and the frequency of max. learning at 15000 as a factor to set up the range of experiment circumstances.

(2) Extraction method of data of learning and experiments

Offensive patterns selected are Left-Running, Right-Running, Center-Running, Corner-Kick and Free-Kick, because among various offensive patterns, those five patterns provide information on the game flow, and their patterns also have an important effect on obtaining goals. In addition, these formations can be clearly distinguished and classified.

4.0 EXPERIMENTS AND ANALYSIS

4.1 Circumstances of Experiments

The experimental environments of this study utilize an IBM compatible Pentium-III class PC, which is equipped with a 440 KHz CPU and 64 MB RAM.

(i) Algorithm: BP algorithm of neural network with three-layered structure.
(ii) Layout of neurons with three layers: One hundred and eight in input layer, eleven in hidden layer and five in output layer.
(iii) Size of field model: 12 in width and 9 in length (based on the FIFA regulation of 120 ×90 meters).
(iv) Number of input neurons: layout of one hundred and eight neurons (determine coordinates value of field model x, y of field model to x=12, y=9).
(v) Use a position vector of a player and ball at ground field model.
(vi) Allocation method of weight to position vector of a player and ball
 (a) Ball = 1.0 and a player with the ball = 0.5.
 (b) A position repeated adds 0.5 to each.
(vii) Normalise the values acquired by allocation method of weight to be between 0 and 1 and draw up as data of learning and experiment.

4.2 Experimental Method Determining the Weight

In a representative frame of scenes, the values of position coordinates and limiting requirements to each object, such as players, ball, etc. are shown. The position value coordinates of the ball and player are set to 1.0 and 0.5, respectively. The position value of the player is incremented by 0.5. The patterns of learning and experiments are of the following five types:

Left-Running, Right-Running, Center-Running, Corner-Kick and Free-Kick. The direction of the pattern used in the test is from left to right on a team basis. The process for data coding is a normalised real value.

4.3 Decision of Weight, Hidden Nodes and Error Tolerance

(i) Decision of Weight of a Player and Ball

The position of the ball is very important in a representative frame of a soccer game. When the ball is in the corner and an offensive player has the same position coordinates as the ball, there is a high possibility of a Free-Kick pattern. The probability of Right-Running would be high if the ball is on the right side on an offensive team, and the position coordinates of players are concentrated on the right. Therefore, the hidden layer was set at eleven, the error tolerance at 001, and, in order to continuously change the weight of a player and ball, the following four patterns are tested, as shown in Table 2.

{ ball=1.0 and a player = 0.3}
{ ball=1.0 and a player = 0.5}
{ ball=1.0 and a player = 0.7}
{ ball=1.0 and a player = 1.0}

Table 2: Experimental results according to the weight of the ball and a player with the ball

Weight / Offensive Pattern	ball = 1.0 player = 0.3	ball = 1.0 player = 0.5	ball = 1.0 player= 0.7	ball = 1.0 player= 1.0
Left-Running	95.0 %	91.7 %	88.3 %	81.0 %
Right-Running	97.9 %	100.0 %	93.2 %	95.9 %
Center-Running	84.7 %	87.5 %	87.5 %	84.7 %
Corner-Kick	100.0 %	97.4 %	97.4 %	94.9 %
Free-Kick	67.3 %	75.0 %	73.1 %	78.8 %

(ii) The Decision of Number of Hidden Layer Nodes

We found that an optimal number of the hidden layer is eleven. We tested the results by changing the node numbers of the hidden layer among 6, 10, 11, 14, 20, 30, 50 and 70 (Table 3), when input layer set to ten, weight of a ball fixed at 1.0, and a player is 0.5.

Table 3: Experimental results of a number of hidden-layer nodes

Hidden layer No. / Offensive pattern	Hidden layer = 11	Hidden layer = 30	Hidden layer = 50	Hidden layer = 70
Left-Running	91.7 %	88.3 %	91.7 %	88.3 %
Right-Running	100.0 %	95.9 %	91.9 %	98.6 %
Center-Running	87.5 %	90.3 %	90.3 %	90.5 %
Corner-Kick	97.4 %	94.9 %	97.4 %	94.9 %
Free-Kick	75.0 %	69.2 %	67.3 %	73.1 %

(iii) The Decision of Error Tolerance

We needed to pay very careful attention to error tolerance, due to its close relation with learning time. In this work, we applied error tolerances of 0.001, 0.002, 0.003, 0.004, 0.005 and 0.006 by crossing (1) and (2) with each other. As a result, the time is greatly reduced when error tolerance is changed from 0.003 to 0.006, but the precision of the learning was very low. If error tolerance is set at 0.002, the learning time is reduced, but if it is set at 0.001 the learning time increases.

Experimental results are shown in Table 4. Based on the above results in this study, we established the most suitable factors heuristically.

Case 1): When a ball became 1.0 and player with a ball 0.5, weight was the most suitable.
Case 2): Nodes of hidden layer are eleven, which is the most suitable.
Case 3): Regarding learning performance, error tolerance was the most suitable when it was 0.001, even though it requires more time.

Table 4: Experimental results based on error tolerance

Error tolerance / Attack pattern	Error tolerance = 0.001	Error tolerance = 0.002	Error tolerance = 0.003	Error tolerance = 0.005
Left-Running	91.7 %	93.3 %	81.9 %	88.3 %
Right-Running	100 %	94.6 %	95.9 %	97.3 %
Center-Running	87.5 %	88.7 %	87.5 %	86.1 %
Corner-Kick	97.4 %	100 %	100 %	94.9 %
Free-Kick	75 %	63.5 %	67.3 %	63.5 %

4.3 Evaluation of Experimental Results

Previous related studies were mainly based on the recognition of information of uniforms to analyse group motion through entire analysis. But the color information of a player could not be recognised well due to noise from the surrounding environment, etc. These studies also had limitations in obtaining exact acquisition of the overall game flow and information of group formations because of correction difficulties by camera movement.

This study has acquired an excellent ratio of recognition using a learning technique of neural networks. Although offensive patterns were the same, the positions of players could be variously changed in a soccer game. This study has learned different patterns of players using the neural networks, resulting in exactness of classification.

The recognition ratio shown was satisfactory. The Right-Running resulted in 100 % recognition, 100% is perfect, and the value speaks for itself anyway, as shown in Table 5. The Free-Kick was recognised at a low level. As shown in Table 6, the Left-Running and the Right-Running tended to be falsely recognised as Center-Running, and we can see the same tendency in observing a representative frame by visual analysis. The problem is that Free-Kick was generally falsely recognised as Left or Right-Running, because it is not clearly distinguished on the representative frame by visual analysis in many cases. As a solution, when data is captured, if the instance starting the Free-Kick is considered as a representative frame, the ball and player with the ball come to have the same coordinates and thus the ratio of recognition could be greatly improved.

Table 5: Recognition rate by offensive patterns

Offensive pattern	Units of data	Number of true recognitions	Number of false recognitions	Recog. rate
Left-Running	6 0	5 5	5	91.7 %
Right-Running	7 4	7 4 (All)	0	100 %
Center-Running	7 2	6 3	9	87.5 %
Corner-Kick	3 9	3 8	1	97.4 %
Free-Kick	5 2	3 9	1 3	75 %

Table 6: Experimental results analysed by offensive patterns

Offensive Patterns	Number of Data	Recognition Patterns					Recog. Rate
		Left - Offensive	Right- Offensive	Center - Offensive	Corner- Kick	Free- Kick	
Left-Running	60	55	0	4	0	1	91.7 %
Right-Running	74	0	74(All)	0	0	0	100 %
Center-Running	72	0	5	63	0	4	87.5 %
Corner-Kick	39	0	0	1	38	0	97.4 %
Free-Kick	52	5	6	1	1	39	75.0 %

The set weight of a player and ball was the most suitable when the ball was 1.0 and a player was 0.5, and the number of hidden layer neurons was 11. An error tolerance of 0.001 gave comparatively good results, but too much learning time was needed (4000~15000 time of learning, 15000 being learning's upper limit). When error tolerance was 0.002 and less, learning time would be greatly reduced (if it is 0.002, the time comes to a max. 3400 from min. 500), but the recognition ratio was 2 to 4 % lower than that of 0.001. Thus the weight of a moving object is set to ball=1.0, a player=0.5, node number of hidden layer to 11, and error tolerance to 0.001, even though learning time would be somewhat longer. The following results denote an analysis of the false recognition of each offensive pattern obtained by experimental results.

(i) Left-Running: Some of the Left-Running offensives were recognised as Center-Running, which is considered a problem of methodology in image taking. We originally planned to use both images, seen from one side and above, but used only the image from the other side, so the position coordinates of each object tended to be recognised as close to center, which is different from Right-Running. If images seen from the side and above are simultaneously used, almost perfect recognition could be expected, as in the case of Right-Running.

(ii) Right-Running: Perfect recognition.

(iii) Center-Running: Center-Running shows a tendency to be falsely recognised. When visually analysed, it is sometimes difficult to distinguish Center Running from a Free-Kick. On our system, such difficulty in distinguishing these patterns also seems to be reflected. In the case of the Free-Kick, if we take measures to recognise the pattern with special features (refer to 'Free-Kick'), the ratio to recognise Center-Running and Free-Kick would be remarkably increased.

(iv) Corner-Kick: One data was falsely recognised as a Free-Kick.
(v) Free-Kick: Most of the Free-Kicks were falsely recognised as Center or Corner-Kicks. When we visually analyse a representative frame in this case, it becomes so unclear that we cannot distinguish it from Center-Running or a Corner-Kick. A solution is that if the instance of a Free-Kick, that is, the instance a player starts to kick a ball, were reflected in selecting a representative frame, the recognition ratio would be considerably increased.

5.0 CONCLUSIONS

In this work, we proposed a classification technique of offensive patterns from group formations to automatically extract soccer highlights from image sequences of a soccer game using neural networks.

Previous studies mainly focused on individual recognition of a player's motion and there has been little work on the recognition of offensives and strategy patterns in a group. Other studies on group behaviour also differed from this research in direction and technique and did not mention any values of the results. Therefore, we cannot compare as it is very difficult to compare our study with other studies using numerical value and experimental results.

The experimental environments of this research were made on an IBM compatible Pentium-III class PC, which was equipped with a 440 KHz CPU and 64 MB RAM. The times required for the experiments were 5~7 minutes for learning time and 5~6 minutes for test time on-line.

A representative frame was selected by automatically segmenting scenes frequently changing on a field, and on the basis of position information of a player and the ball. We traced group formations during the game and analysed the group behaviour. Using a BP algorithm of neural networks technique for automatic recognition and classification of offensive patterns, we laid the groundwork to automatically extract soccer highlights.

Data sets used as representative frames totaled 297 in this experiment; Left-Running was 60, Right-Running 74, Center-Running 72, Corner-Kick 39, and Free-Kick 52. Experimental results showed quite a good rate of recognition: Left-Running reached 91.73 %, Right-Running 100 %, Center-Running 87.5 %, Corner-Kick 97.4 % and Free-Kick 75 %. Future plans are to develop evaluation techniques of a player's ability, automatic extraction of data under natural circumstances, automatic tracking of group formations, and to eventually build a practical system for automatic extraction of reliable soccer highlights.

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