Grey Decision-Making for a Billiard Robot

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Abstract- *Billiard is one of the most complex game to play in the real world. A player needs to visualize the situation between balls and pockets and to score the ball into the designate pocket by his/her own experience. A billiard robot is developed to imitate the behavior of human beings to play billiard. There are machine vision, decision-making, control and actuating subsystems in the experiment setup. The objective of this paper is to design a decision algorithm for a billiard robot by using grey theory. The results indicate that the decision algorithm work very well in both the simulation and experiment.*

Keywords：billiard robot, grey decision-making

1 Introduction

The billiard is one of the amusing activity for years. The game of billiard is played on a rectangular table (billiard table). One ball (cue ball) is struck with the end of a cue stick, causing it to bounce into other balls and reflect off the side of the table. A good player needs to have capability of precise geometry concept and strategy to win the game. This paper presents a grey decision algorithm for our developed billiard robot.

There are several software packages that simulate the billiard game in virtual environments. Koo applied the concept of fuzzy logic to develop the decision algorithm on computer generated pool environments[1]. Recently, researches have been carried out to create intelligent robotics in many applications[2-3]. It is necessary to have the vision, image processing, decision-making, control and actuating subsystems in such a robot. Some published papers shown parts of the above functions of a billiard robot. Koo demonstrated the balls identification and calibration for a pool robot by the image processing technique[4]. Nakama developed a shooting mechanism for a billiard robot by a precise position mechanism[5]. A wearable computer and augmented reality has demonstrated to help players to enhance the game of billiards[6]. All of them are lack of the integration both of strategic part and electro-mechanical part.

Grey system theory was disclosed by Prof. Deng in 1982 [7]. It can be applied to deal with uncertainty, and incompleteness of a system. This theory can explain a system with incompleteness of information via grey methodologies, including grey modeling, grey prediction, grey relational analysis, and grey decision making [8].

In the research, the geometrical positions of the cue ball, object balls and six pockets are obtained by a CCD camera and an image capture card automatically. Then the developed grey decision algorithm is applied to find out the priority of the candidate object ball and the corresponding pocket. Then, the hitting point of the first object ball is determined by the cut-shot controller based on the technical information of billiards. Finally, the shooting command is sent to the 5-axes actuating mechanism to sink the object ball into the designate pocket successfully(Fig.5).

2 Grey Decision-Making

2.1 Decision algorithm for one object ball

We assume that there are a cue ball and a color ball (object ball) on the billiard table for simplification. The geometric locations of the two balls and six pockets are obtained by the vision subsystem with a CCD camera, image capture and processing software. There are two geometric parameters to estimate the decision index of a shot on the billiard table. The first is the distance d_i between the object ball and the candidate pocket i. The second is the angle α_i of the candidate pocket i with respect to the object ball. Figure 1 shows that the angle β between the object ball and the cue ball is constant.

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To sink the object ball into the designate pocket is depend on those two parameters. If the distance d_i is smaller, it is easier to sink the object ball into the designate pocket. If the closer of angle α_i to angle β, it is easier to sink the object ball into designate pocket. So, the decision algorithm is determined by the combination of the effect of the distance d_i and the effect of the angle difference between α_i and β. It is said that there are two evaluating factors in the grey decision making subsystem for this case.

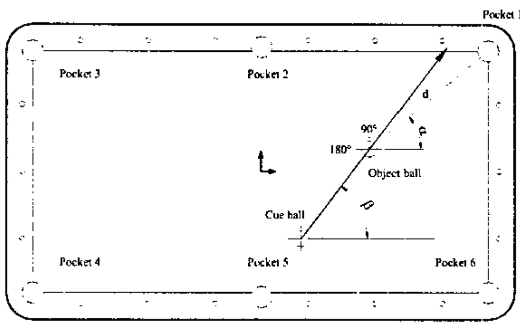

Figure 1. A cue ball and an object ball on a billiard table.

(i) Factor r_{1i}: evaluating the effect of the distance d_i between the candidate pocket i (i=1~6) and object ball. Because the distance d_i is the smaller the better, so the lower effect measurement of distance parameter is [8]

$$r_{1i} = \frac{\min_i \{ d_i \}}{\{ d_i \}} \qquad (i=1\sim6) \tag{1}$$

(ii) Factor r_{2i}: evaluating the effect of the angle α_i. α_i (i =1~6) represents the angle of the candidate pocket i with respect to the object ball. β is the angle of the object ball with respect to the cue ball(Fig. 1).

When a ball gets a direct hit from the cue ball, the hitting angle is known as 0°. That is $\alpha = \beta$. In practice, the cutting angle is 0° to 90° right and 0° to 90° left (Fig. 2). Therefore, the factor r_{2i} is calculated by equation (2).

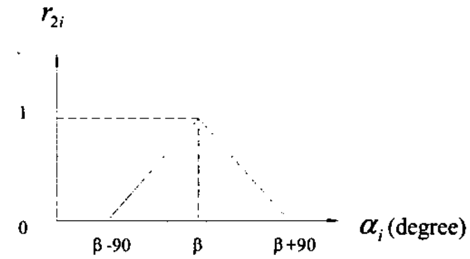

Figure 2. The target effect measurement of target angle β

$$\begin{cases} \text{if} & \alpha_i \geq \beta + 90 & \text{then} & r_{2i} = 0 \\ \text{if} & \beta + 90 \geq \alpha_i \geq \beta & \text{then} & r_{2i} = \dfrac{(\beta+90) - \alpha_i}{90} \\ \text{if} & \beta \geq \alpha_i \geq \beta - 90 & \text{then} & r_{2i} = \dfrac{\alpha_i - (\beta - 90)}{90} \\ \text{if} & \alpha_i \geq \beta - 90 & \text{then} & r_{2i} = 0 \end{cases} \tag{2}$$

Finally, the decision index of a shot is calculated form above two factors by equal weight. Let D_i represents the decision index of a shot from the object ball to candidate pocket i.

$$D_i = 0.5(r_{1i} + r_{2i}) \qquad (i = 1 \sim 6) \tag{3}$$

if $D_k = \max_i \{D_i\}$, then the candidate pocket k is the designate pocket of this shot. Here is an example to demonstrate the calculation by this grey decision algorithm (Fig.1, Table 1). If the geometric locations of the cue ball and the object ball are like those in figure 1 (α =25.66°, β=28.61°, d=198.58 pixel). We can get geometric information from the vision subsystem. The data are listed in table 1.

Table 1. Parameter data of Fig.1

Parameter / Candidate i	d_i (pixel)	α_i (degree)
1	198.58	25.66°
2	204.28	150.04°
3	549.62	169.82°
4	607.45	205.34°
5	333.66	236.74°
6	320.08	303.45°

where $\min_i \{d_i\} = 198.58 = d_1$

$$r_{1i} = \frac{\min_i \{d_i\}}{\{d_i\}} = \frac{198.58}{\{d_i\}}$$

$r_{11} = 1$, $r_{12} = 0.972$, $r_{13} = 0.361$, $r_{14} = 0.3269$, $r_{15} = 0.595$, $r_{16} = 0.620$

Form equation (2), $\beta = 28.61°$ and $\alpha_1 = 25.66°$(table 2)

$$r_{21} = \frac{\alpha_1 - (\beta - 90)}{90} = \frac{25.66 - (28.61 - 90)}{90} = 0.967$$

Similarly, we can get the $r_{22} = 0$, $r_{23} = 0$, $r_{24} = 0$, $r_{25} = 0$, $r_{26} = 0$

Finally, the decision grade D_i is calculated by equation (3) and listed in table 2.

$$D_1 = \max_i \{D_i\} = 0.984$$

Therefore, the pocket 1 is the designate pocket for this example from the results (Table 2).

Table 2. The data of decision factors r_{ij} and decision index D_i

	Pocket 1	Pocket 2	Pocket 3	Pocket 4	Pocket 5	Pocket 6
Factor 1 γ_{1i}	1	0.972	0.361	0.326	0.595	0.620
Factor 2 γ_{2i}	0.967	0	0	0	0	0
Decision grade D_i	0.984	0.486	0.180	0.163	0.297	0.310

2.2 Decision algorithm for multiple object balls.

We assume that there are a cue ball and five candidate object balls on a billiard table(Fig.3). The image processes are similar to the previous case. The corresponding candidate pocket is determined by the previous decision algorithm (section 2.1). The estimating parameters of this decision algorithm are (1)the distance d_i between the object ball i and the corresponding pocket, (2)the angle θ_i of the corresponding pocket with respect to the object ball i, and (3)the distance l_i between the cue ball and object ball i.

Similarly, there are three evaluating factors in this decision algorithm.

(i)Factor r_{1i} : evaluating the effect of the distance d_i. Because d_i is the smaller the better, the lower measurement of this distance parameter is the same as equation 1.

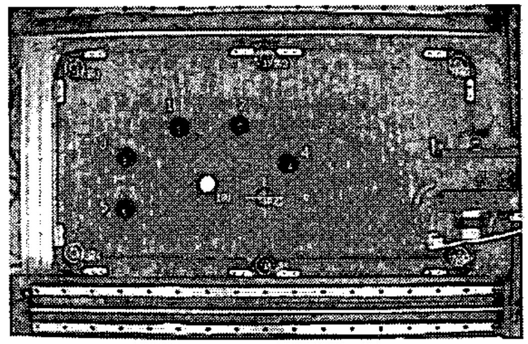

Figure 3.One cue ball and 5 object balls on a billiard table

(ii)Factor r_{2i} : evaluating the effect of the angle θ_i. Similarly, the target measurement is applied to this factor.

$$\begin{cases} if & \theta_i \geq \beta_i + 90 & then & r_{2i} = 0 \\ if & \beta_i + 90 \geq \theta_i \geq \beta_i & then & r_{2i} = \dfrac{(\beta_i + 90) - \theta_i}{90} \\ if & \beta_i \geq \theta_i \geq \beta_i - 90 & then & r_{2i} = \dfrac{\theta_i - (\beta_i - 90)}{90} \\ if & \theta_i \geq \beta_i - 90 & then & r_{2i} = 0 \end{cases} \quad (5)$$

where $i = 1 \sim 6$, β_i is the angle of the object ball i with respect to the cue ball.

(iii)Factor r_{3i} : evaluating the effect of the distance l_i. Form the experience of billiard players, the distance l_i can not be too small for a cut shot. Therefore, the target measurement is applied to this factor (Fig.4).

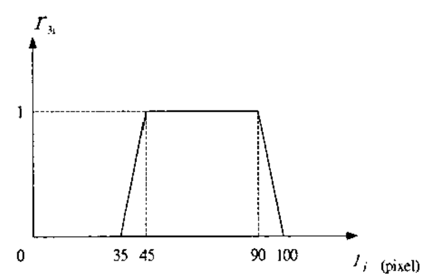

Figure 4. The target effect measurement of distance l_i.

$$\begin{Bmatrix} if & l_i \geq 100 & then \; r_{3i} = 0 \\ if & 100 \geq l_i \geq 90 & then \; r_{3i} = \dfrac{100 - l_i}{10} \\ if & 90 \geq l_i \geq 45 & then \; r_{3i} = 1 \\ if & 45 \geq l_i \geq 35 & then \; r_{3i} = \dfrac{45 - l_i}{10} \\ if & l_i \geq 35 & then \; r_{3i} = 0 \end{Bmatrix} \quad (6)$$

Finally, the decision index of a shot is calculated form above three factors by equal weight.

$$D_i = \frac{1}{3}(r_{1i} + r_{2i} + r_{3i}) \tag{7}$$

If $D_k = \max_i\{D_i\}$, then the candidate object ball k is in the first priority to be shot. The example of figure is shown on the table 3 and 4.

Table 3.Peramter data of Fig.3

Candidate object ball i	Corresponding pocket	d_i (pixel)	θ_i (degree)	l_i (pixel)
1	Pocket 3	147.2	140.7°	80.22
·2	Pocket 2	87.99	78.8°	85.5
3	Pocket 3	106.73	123.5°	106.7
4	Pocket 1	244.5	45.2°	106.85
5	Pocket 4	78.88	235.7°	107.3

Table 4.Data of decision factor γ_{ij} and decision index D_i

	Object ball 1	Object ball 2	Object ball 3	Object ball 4	Object ball 5
Facfor1 γ_{1i}	0.53	0.896	0.626	0.322	1
Facfor2 γ_{2i}	0.6033	0.7089	0.7944	0.3356	0
Facfor3 γ_{3i}	1	1	0	0	0
D_i	0.7111	0.8683	0.4735	0.2192	0.3333

The result indicates that D_2=0.8683 is the maximum value of this example. Therefore, the candidate object ball 2 is the easiest ball to be sink into pocket 2 form this grey decision algorithm

3 Experiment and Result

3.1 Experiment

The billiard robot system includes a machine *vision subsystem, decision-making subsystem, control* and actuating subsystem (Fig 5, 6). The billiard table is an one-sixth miniature table.

In the experiment, the position of the cue ball, object balls and pockets are caught and calculated by the vision subsystem first. Then, the simulate results of the grey decision-making system are shown on the graphic user interface(GUI) in PC (Fig. 7). The hitting point of the object ball is determined by the cut-shot controller. Finally, the shooting command is sent to the actuating mechanism to sink the object ball into the designate pocket.

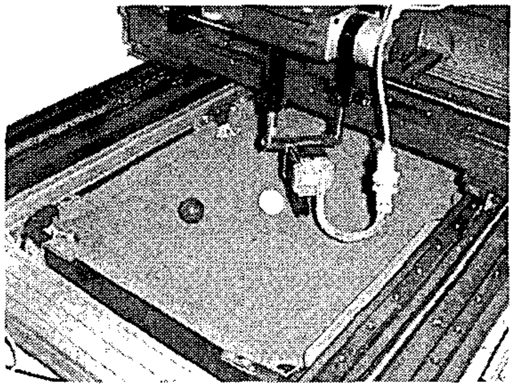

Figure 5 Experimental setup

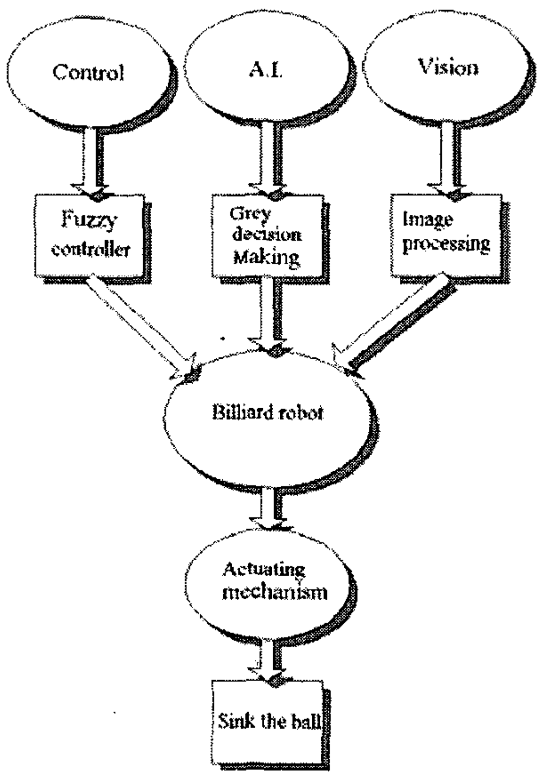

Figure 6 Flow chart of this billiard robot

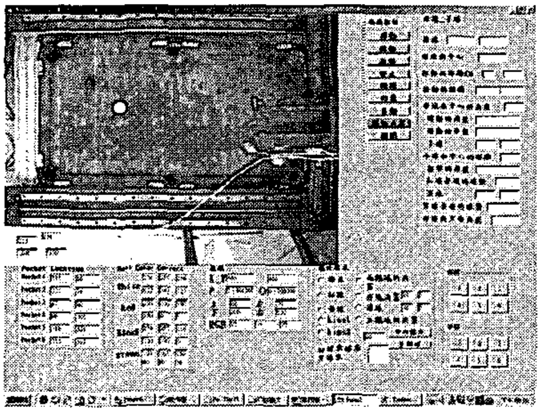

Figure 7. A VB GUI example

3.2 Result

Figure 8 shows the experimental results of one cue/one object ball case in 16 picture taken by a digital camera continuously. The picture 1 to 9 shows that the actuating mechanism is in the stand by situation before the shot. The actuating mechanism begins to hit the cue ball in picture 10. The object ball moves in the direction toward the designate pocket in picture 11. The cue ball moves to the new position after this shot(pictures 12-16).

The experiment results of one cue/five balls case are show in Fig 9. The billiard robot is in the stand by situation before the shot (picture 1-6). The cue ball is hit by the actuating mechanism and make the object ball move into the corresponding pocket in picture 7. Then, the cue ball moves to the new position after this shot (picture 8-16).

4 Conclusion

In the research, we put a cue ball and up to five object ball on the billiard table. The simulate results show that the developed grey decision-making subsystem work very well in the GUI. And the developed billiard robot shows its ability to "read the table" and find its own decision to sink the candidate object ball into designate pocket automatically and successfully.

In the near future, we hope to modify this billiard robot to enhance some advance skills. For example, they are bank shot, jump shot, and position play to clear up the table.

Acknowledgements

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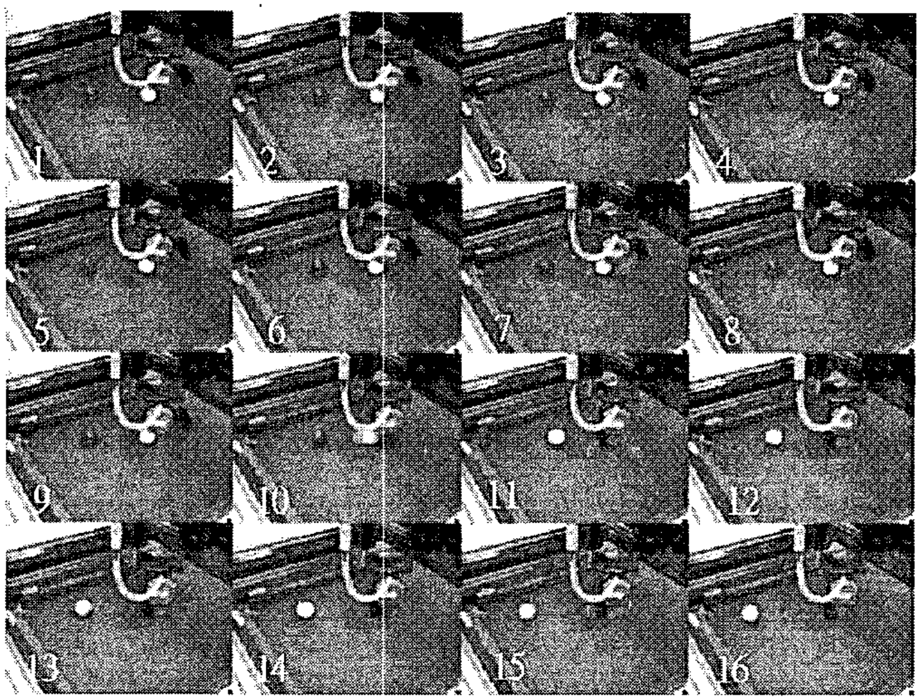

Figure 8. The 16 pictures taken by a digital camera continuously

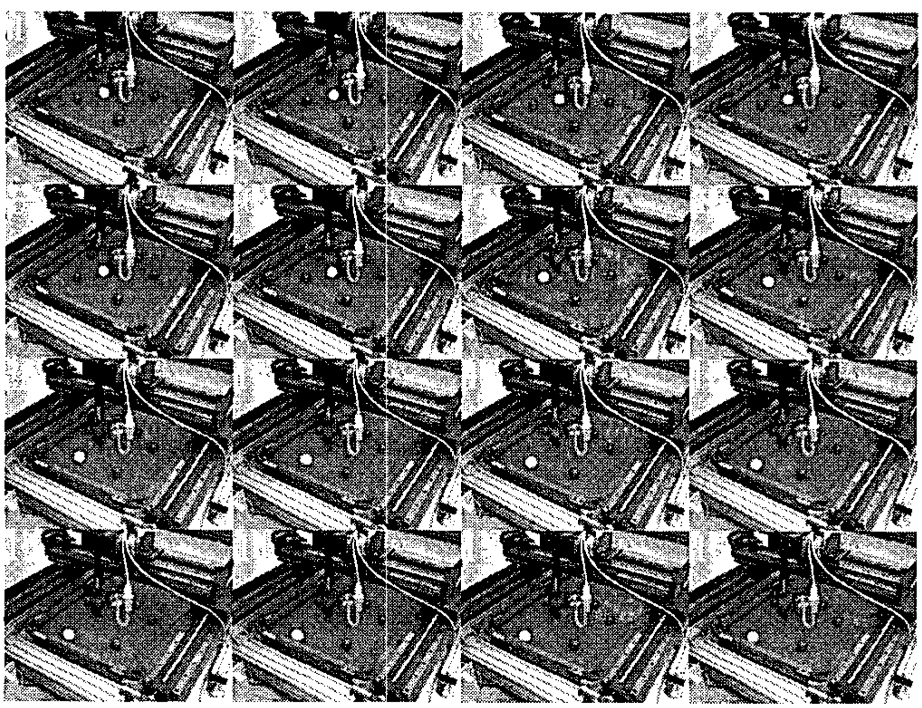

Figure 9. The 16 pictures taken by a digital camera continuously