Analysis of Humans' Tactical Limitation in Computer Driving Game

Tao Shang
Kochi University of Technology
185 Miyanokuchi, Tosayamada-cho,
Kami-gun, Kochi 782-8502,JAPAN
email:076012j@gs.kochi-tech.ac.jp

Shuoyu Wang
Kochi University of Technology
185 Miyanokuchi, Tosayamada-cho,
Kami-gun, Kochi 782-8502, JAPAN
email:wang@mech.kochi-tech.ac.jp

Abstract: **In this paper, we conjecture that the action techniques of humans can help overcome the pathfinding problem for strategy games. In order to analyze the action tactics of humans, we extend an empirical driving game to a more complex class of games by mean of simulation methodology. Firstly, the two concepts of relationship function between objects and decision matching rate (DMR) are defined, then two explorations in progress are described: how humans make tactics under complex environments with multiple obstacles and whether there exists humans' tactical limitation for obstacle avoidance. The resulting tactics and tactical limitation will be applicable in turn to strategy games, and into relevant path planning.**

Ⅰ. INTRODUCTION

PC and console entertainment systems are increasingly fused into people's daily lives. For games to achieve its promise as a rich and popular entertainment form, we believe it will be necessary to explore well to those issues of developing computational theories for cognitive and emotional agents beyond entertainment, because in games the individual's choice is essentially a choice of a strategy at best mixed motives. If such interactive strategies could be obtained, they would not only provide guide with the design of more striking games, but also the analysis method of humans' intelligent action would promote the development of other domains. For example, game theory is combined into decision making mechanism for autonomous multiple agents system [1]; the qualitative battlespace representation and reasoning work are implemented in computer games for the acquirement of tactics to support US military needs [2]. On this interpretation, a study of games may indeed tell us something about serious interactions. But how much? This paper extends an empirical driving game into a simulation system by computer [3]. It allows us to observe purely adaptive behaviors of players in games, to observe differences of behavior due to changes in games' parameters, and to discover new strategies for playing games. We will try to analyze the action tactics of humans under complex environments and seek the limitation of obstacle avoidance.

Meanwhile, the danger evaluation will be discussed here. Intelligent behaviors of humans depend on humans' subjective evaluation to an environment: in an environment what are dangerous or safe conditions? Such theory will not only help completely substitute drivers in autonomous driving [4], but contribute to the development of an automobile driving support system as well [5,6]. Until now, many works have been conducted in the research of danger evaluation. Danger is evaluated by using a fuzzy reasoning method for robot control [7,8] and advanced safety automobile [9]; collision danger is defined by using errors of position and environmental modeling in the environment with static objects, but distance is the only essential factor for the evaluation of danger [10]. Of course, it is difficult for us to evaluate danger degree of an environment by using one simple formula, however, it is relatively easier for us to evaluate the danger relationship between two objects in the environments by formula. Hence, the relationship function between objects is defined to represent humans' subjective evaluation here.

Firstly, we introduce the driving game; next, define the concepts of relationship function between objects and decision matching rate; then from two viewpoints of static obstacles and mobile obstacles we discuss humans' action tactics in different environments.

Ⅱ. DRIVING GAME

Facing the rectangle simulation environment, a player can control the speed and direction of a virtual agent by handler and pedal. Border bump is treated as simple elastic bump. A goal and agent are denoted by filled circles, while an obstacle is denoted by filled rectangle.

The motion of a virtual agent acts on the equation of motion just as follows:

$$m\ddot{Y} + D\dot{Y} = F \tag{1}$$

where

- m is the quality of the agent,10 kilogram;
- $Y = (y_1, y_2)^T$, which is the position of the agent;
- $\dot{Y}, \ddot{Y}$ is the speed and acceleration of the agent, respectively;
- D is the coefficient matrix, here, each item equals 0.7 decided by practical performance;
- F is the driving force from a pedal and handler.

The attributes of obstacles, including size, position, and speed vector, can be chosen by players. So can the starting point and the goal of an agent.

A game is treated as successful game, only if the virtual agent controlled by a player arrives at a goal point from a starting point with free collision during the appointed time limit; otherwise, it is treated as failed one.

Players have to consider three distinct sources of constraints to act in the driving game. First, trafficability concerns the ease with which an agent can move along the path; second, visibility describes how well it can see the environment. Most of computer games appear to limit visibility in order to increase difficulty level of a game. Here, players' path finding is most visible: players have access to all the information they need plus time in order to sufficiently embody players' intelligence: global tactics and local tactics; third, reward will be distributed on basis of players' activity. The reward principles are described below by importance: successful driving is basis for game; a shorter path is granted a larger reward; a shorter time is granted a larger reward.

III. DEFINITION

A. Relationship function between objects

The concept of relative relationship between objects η is defined to evaluate the relative relationship between two objects,

$$\eta(o_1,o_2) = f(D_r,V_r,\alpha_r) = ke^{-(\alpha_r/180)} * (|V_r|+1)/(D_r+1) \tag{2}$$

where o_1,o_2 denote two objects in an environment;

D_r denotes the distance between o_1 and o_2;

V_r denotes the relative speed between o_1 and o_2;

α_r denotes the angle between the relative speed of current object o_1 to object o_2 and the position vector of two objects; when the speeds of o_1 and o_2 are zero, it is required to be zero;

k is the coefficient for adjustment.

This formula (2) can appropriately describe the relative relationship between two objects, regardless of static or mobile objects. When o_1 is the agent of a player and o_2 is an obstacle, this relationship function represents the danger degree generated by o_2 to the agent o_1. Generally, if D_r is smaller, the danger degree is larger; if V_r is larger, the danger degree is larger; if α_r is smaller, the danger degree is larger.

On the other hand, when o_1 is an agent and o_2 is a goal, this relationship function represents the safety degree generated by o_2 to the agent o_1.

In the latter part we will use Danger Degree to analyze the players' strategies.

B. Decision matching rate(DMR)

In order to investigate the similarity and ignore the minute difference of players' decision in different runs, the concept of decision matching rate (DMR) is defined here.

Firstly, a decision vector is denoted as $V=(v_1,v_2,v_3,\cdots,v_n)$, where v_i is a decision mark; n is the total number of elements in a decision vector.

For two decision vectors v^1, v^2, the decision matching rate of theirs is defined just as follows:

$$DMR(v^1,v^2)=\left(\sum_{k=1}^{L} p_k^{12}\right)\Big/L, \quad p_k^{12}=\begin{cases}1, v_k^1 = v_k^2\\ 0, v_k^1 \neq v_k^2\end{cases} \tag{3}$$

$$L=\begin{cases}min(n^1,n^2),\ min(n^1,n^2)>2\\ max(n^1,n^2),\ others\end{cases}$$

Where the use of $min(\ )$ can avoid redundant decisions around a goal point when an agent fails to arrive at the goal point for the first time, so under the environment with static obstacles $min(\ )$ is always adopted for the reason of high success rate, while $min(\ )$ and $max(\ )$ are both adopted under the environment with mobile obstacles for the reason of lower success rate.

By virtue of decision matching rate, the decision matching method is also introduced here just as follows:

Step1: Set the threshold value δ in order to avoid the zero fluctuation of a handler and obtain the decision representing the main intention of a player;

Step2: Save the decision sequence to a separate file in each experiment;

Step3: Compress the decision sequence to the decision vector, which is not related to time and just represents direction change, that is, the continuous same decisions are denoted by one decision mark;

Step4: Compare two decision vectors decision vectors by (3), the result is treated as the decision matching rate of these two decision vectors.

IV. TACTICS OF PLAYERS IN THE ENVIRONMENT WITH STATIC OBSTACLES

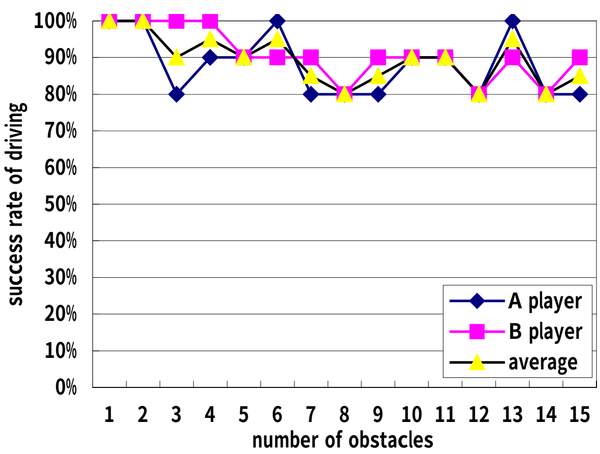

Fig. 1 Relationship between success rate of driving and the number of static obstacles

(20 times per case, 300 times per player)

Besides the constraints of section II, the experimental conditions are: the average age of players is 28.5 years old; the initial positions of a player and goal point are fixed, whereas the positions of obstacles are distributed at random. The area proportion between an obstacle and an agent is 16:1; the maximum number of permissible obstacles in capacity of environment is 140.

From Figure 1 we can know that the high average success rate of driving, which is larger than 80%, keeps stable no matter how many obstacles exist in game environment. Furthermore, it can be said that based on the experimental conditions, the success rate of driving is probably not relevant to the number of obstacles under the environment with static obstacles (total number ≤ 15), that is, to concern one obstacle is equal to concern multiple obstacles. Of course, it is the most meaningful tactics for a player to concern the only current obstacle and act only by switching the case of current obstacle, if only one obstacle is concerned for making decision.

In order to further define Current Obstacle, we shall not only use the above described danger degree, but also analyze the characteristics of players' tactics.

A. Characteristics of players' tactics

According to the above mentioned constrains, a typical experiment shown in Figure 2 was conducted by 10 players, respectively. We will illustrate the analysis process via the corresponding data of decision matching rate listed in Table 1 and Table 2. Direction decision includes three types of marks: F(forward), L(left),and R(right). Change pattern of decision includes four types of FL, FR, RF, and LF. In order for data separation, decision matching is implemented between separate experiments, not continuous experiments.

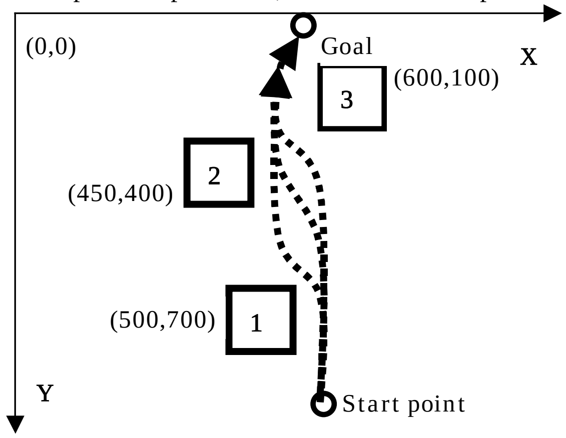

Fig. 2 Experimental scenario

Table 2 Average DMR of 10 players (δ =10)

Order of players	Average Decision Matching Rate
1	86.8214%
2*	76.3334%
3*	72.1389%
4	80.0000%
5	86.1539%
6*	85.9524%
7	71.6667%
8	89.1667%
9	76.0000%
10	92.3546%
Average	81.6588%

(* denotes the player with driving experiences)

Table 1 illuminates the generation procedure of decision matching rate of the first player. Table 2 indicates the high recurrence of decision (larger than 80% average decision matching rate) regardless of whether the players own driving experiences. Therefore, it is possible that players can easily make global planning before action happens under the environment with static obstacles, rather than just blindly doing concrete tasks. Therefore, it can be said that recurrence is the characteristic of players' tactics under environment with static obstacles.

B. Current obstacle

In order to illuminate the definition of current obstacle, on basis of the recurrence characteristics of players' tactics and appropriate description of danger degree between an agent and an obstacle by using relationship function, rationally the most dangerous obstacle should be considered by players, therefore, we can define the current obstacle for human decision is the obstacle satisfying the condition $\{i \mid \max(\eta_i), i \in [1, \cdots, n]\}$, n is the total number of obstacles in an environment. Figure 3 shows the variation of current obstacle from 1 to 3 in an example of Figure 2 scenario by using maximum danger degree.

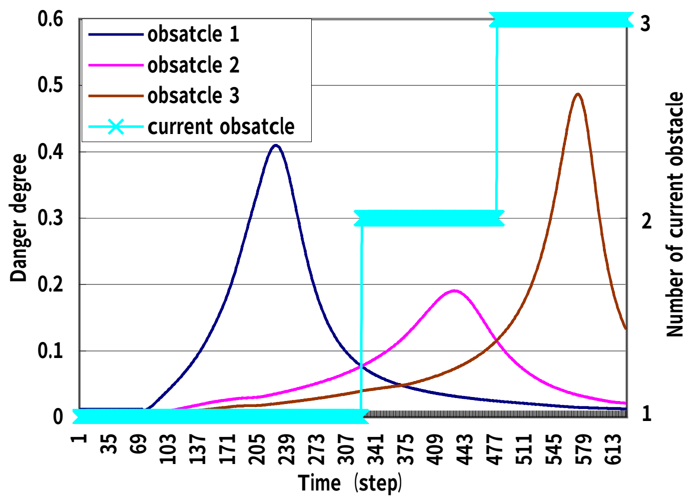

Fig. 3 Variation of danger degree and current obstacle

In fact the path generated according to current obstacle is a safety path. If integral calculus of danger degree at all position is calculated as (3):

$$E = \int_L \left(\sum_{i=1}^{N} \eta(o_A, o_i, x) \right) dx \qquad (3)$$

Where L is the generated path, N is the number of obstacles. The path minimizing E is the safest path, so it is feasible to evaluate and design a path by danger degree.

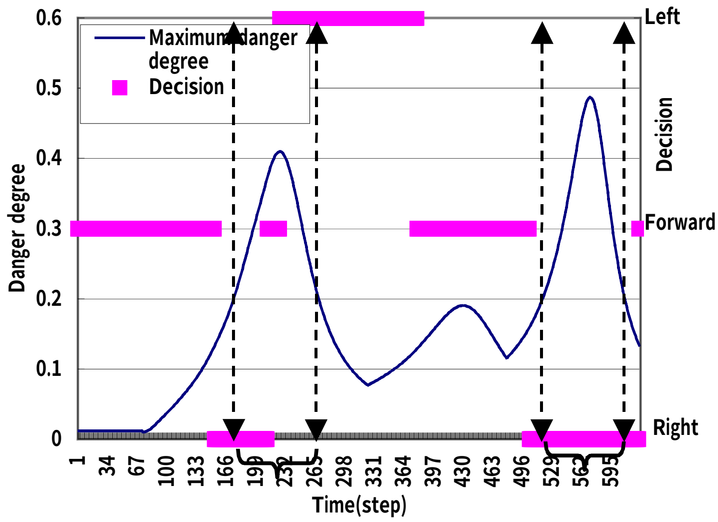

Fig. 4 Maximum danger degree and decision selection

Furthermore, according to maximum danger degree, if a given threshold is chosen, for example, 0.2 in Figure 4, the

Table 1 DMR of 1th player (δ =10)

No.	DMR	Decision vector									
0		F	R	F	L	F	L	F	R	F	R
Length		134	64	10	126	55	61	38	146	34	32
1	83.3333%	102	70	14	25	1	R228				
2	90.0000%	72	54	9	122	48	179	29	121	68	L22
3	83.3333%	37	53	22	118	215	R90				
4	100.0000%	39	50	9	106	55	110	61	173	16	
5	87.5000%	60	55	10	180	82	R125	32	64		
6	87.5000%	55	64	17	119	181	112	15	L73		
7	83.3333%	43	54	5	195	127	R171				
8	87.5000%	67	51	8	261	15	R114	26	73		
9	80.0000%	31	52	7	305	34	R59	13	164	4	L181
10	85.7143%	92	45	9	124	149	R123	5			
Average DMR		86.8214%									

(F/L/R+number: F/L/R denotes different decision, number denotes the length of same decisions)

unconscious decision from a player can be filtered when situation is not dangerous enough so that rational decision from a player, just as the two chosen sections in the below part of Figure 4, can be obtained for further knowledge analysis.

V. Tactics of Players in the Environment with Mobile Obstacles

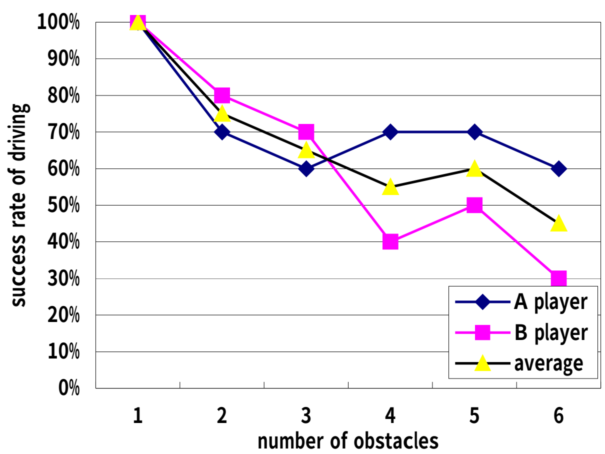

Fig. 5 Relationship between success rate of driving and the number of mobile obstacles (20 times per case, 120 times per player, speed V=2 pixels/10ms)

On basis of Figure 5, as the number of obstacles increases from 1 to 6, the average success rate of driving will obviously decline from 100% to 45%. Furthermore, two points are summarized:

1.) The number of obstacles has impact on driving, so it is possible that there is direct relationship between success rate of driving and the number of obstacles, that is, it is necessary to concern not only one obstacle simultaneously, but multiple obstacles for decision;
2.) From the viewpoint of success rate of driving, the success rate of driving is too low when there are too many obstacles in the environment, that is, it is true that there does exist limitation of obstacle avoidance for a player.

Hence, current obstacle is extended into current obstacle group that consists of obstacles with maximum danger degree within the number of identifiable obstacles. It is the most meaningful tactics for a player to concern the current obstacle group for obstacle avoidance and act only by switching the case of current obstacle set for making decision. For our research, the important conclusion is that under the environment with mobile obstacles, we try to find the upper limitation of the number of identifiable obstacles and extract the knowledge within limitation of humans.

By Figure 5, based on the experimental condition, the upper limitation of identifiable obstacles in case of mobile obstacles is 5 if the satisfactory success rate of driving is 50%.

Next, we will discuss the impact of speed of obstacles on driving performance. Figure 6 shows that the success rate of driving for a player will fluctuate in the variation scope of 40% with the increasing speed of obstacles from 2 to 10, while the success rate obviously decreases with the increasing number of obstacles from 2 to 8. It is evident that the speed of obstacle has no larger impact on performance than the number of obstacles.

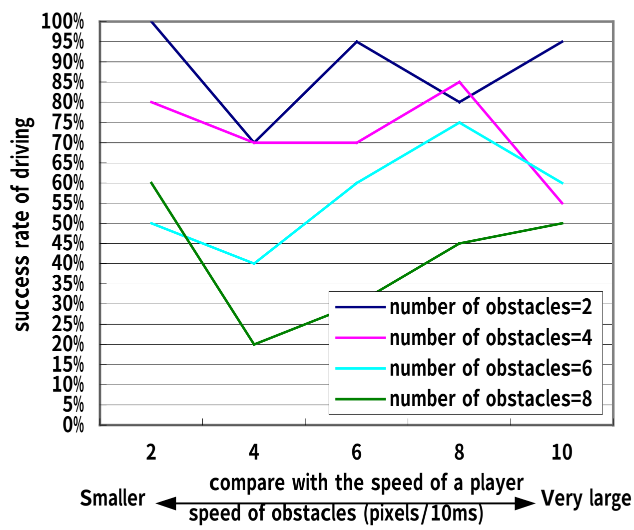

Fig. 6 Mobile obstacles with variable speed (20 times per case, total number is 400 times)

Table 3 shows that the corresponding decision matching rates of all players decrease by larger than 20% average DMR variation under the environment shown in Figure 7. By combination with figure 5, it suggests that as failures increase, the recurrence of tactics will be no more obvious under the environment with mobile obstacles, which means that the factor of motion restricts global planning before action. Players usually attempt to select optimal action scheme through concrete action. Meanwhile, It indicates that under the environment with mobile obstacles players have the limitation of obstacle avoidance to act and cannot judge the mobile environment more properly than under static environment.

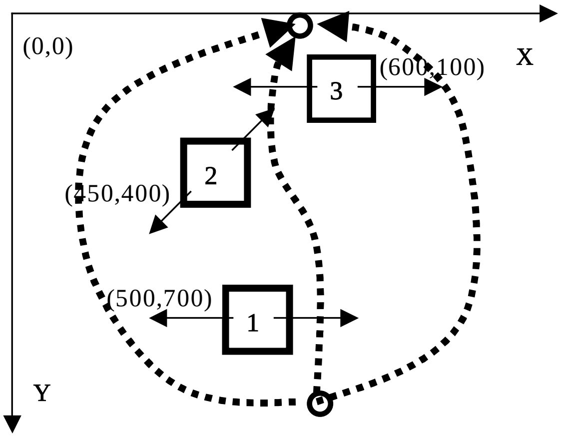

Fig. 7 Experimental scenario (speed V=3 pixels/10ms)

Table 3 Average DMR of 10 players ($\delta = 10$)

Order of players	Average Decision Matching Rate(DMR)	Variation of DMR
1	57.5000%	-29.3214%
2*	63.3334%	-13.0000%
3*	68.6616%	-3.4773%
4	72.5000%	-7.5000%
5*	64.3367%	-21.8172%
6*	60.1769%	-25.7755%
7	67.3642%	-4.3025%
8	20.0000%	-69.16667%
9	57.5000%	-18.5000%
10	72.3095%	-20.0451%
Average	60.3682%	-21.2906%

(* denotes the player with driving experiences)

VI. GUIDELINE FOR GAME

According to game theory [11], a strategic game is modeled as: $\{N, A_i, \geq i\}$, where N defines the set of agents, A_i is the set of actions available to agent I, $\geq i$ is a preference relation of agent i , under a wide range of circumstances. The preference relation can be represented by a utility function u_i . Based on the serious interactions of game theory, the limitation of boundedly rational agent can simplify the design of utility function u_i . Even for the games based on reasoning system, we will use such limitation of players to acquire the knowledge of humans as much as possible to fulfill the reasoning part of a game: under the environment with static obstacles, it is enough to extract the knowledge under the environment with one obstacle; under the environment with mobile obstacles, it is enough to extract the knowledge within limitation of humans for obstacle avoidance. Of course such conclusion can be used for the other development involving human information processing model.

VII. CONCLUSION

In this paper we have described work in progress on using humans' tactics to improve artificial intelligence for pathfinding in strategy games. The central idea is that by defining relationship function between objects and decision matching rate, from two viewpoints of static obstacles and mobile obstacles we discuss humans' reusable action tactics: under the environment with static obstacles, on one way, in term of global tactical level, humans can easily make tactics before action so that decision has the characteristics of recurrence; on the other hand, in term of local tactical level, humans act on the current obstacle satisfying maximum danger degree; under the environment with mobile obstacles the recurrence of decision is not obvious any more, and success rate of driving is subject to limitation of humans' tactics. This limitation can be quantified to some game parameters such as number and speed of obstacles. The number of obstacles is most important factor.

We are currently proceeding in this research in two ways. First, we are continuing to experiment with this computer game, to verify the limitation description to support path-finding and deeper environment analysis. Second, working with simulation system, we are extracting rule base of humans' tactics so that the resulting rules can more realistically describe the action intelligence of humans.

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