Vehicle Navigation Strategy based on Behavior Fusion

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ABSTRACT

In this paper, a new navigation strategy based on the fusion of various behaviors to enable mobile vehicles to navigate in an unknown environment is described. The aim of this research is to fuse the two independent and sometimes conflicting behaviors: obstacle avoidance and goal seeking, such that the vehicle efficiently performs obstacle avoidance while seeking it's goal. The balance between these two behaviors is achieved by combining the control actions from the goal seeker and the obstacle avoidor through evaluating the goal vector magnitude, the minimum distance detected by the ultrasonic sensors, and the distance to the obstacle in the direction of the goal vector. Furthermore, an environment evaluator is used to enhance the adaptability of the navigator by tuning the universe of discourse of the sensor space. The new navigation strategy has been verified to be efficient in an indoor virtual environment.

1. INTRODUCTION

The control architectures for mobile vehicles proposed to date may be classified into two categories: *function decomposition* and *behavior based decomposition.* Traditional function decomposition used a SMPA (Sense-Model-Plan-Act) framework. It consists of modules each of which senses the world, builds a world model, and plans actions for the vehicle. These modules are connected in a serial sequence. Although there are some successful examples [1, 2] for this architecture, a serious shortcoming is its unreliability. The entire system may break down if any one module fails. i.e., it lacks robustness.

On the other hand, behavior based decomposition or behavior control, decomposed the system into special task-specific modules, each of which are connected directly to sensors and actuators and operates in parallel. These modules are usually called *behaviors.* All *behaviors* are connected by an arbitrator to determine the control action of the entire system. Such architecture at least have three advantages: First, it can react to contingencies in real time due to the parallelization. Second, as each *behavior* is task specified, it could be very simple, which can be easily and flexibly managed, e.g., add or remove a behavior. Third, it has good robustness, i.e., the system can still function even if one or more of the *behaviors* fail.

A number of behavior control methods have been proposed [4,5] since the first behavior control architecture proposed by Brooks [3]. Commonly, *behaviors* are reactive among these methods. A typical example is the potential field method [6,7]. However, the problems of local minimum and unstable motion [8], limit it's application. Recently, Fuzzy logic [9,10,11] and neural network [12,13] are being utilized to construct the reactive *behaviors* for navigation. These two approaches have their merits and drawbacks. In order to combine their strength, we have proposed a reliable method [14] which used reinforcement learning to construct the fuzzy rule base for the obstacle avoidance *behavior*.

When multiple *behaviors* are used to control the same actuator simultaneously, they have to be fused by some form of arbitration mechanism which allows the independently developed *behaviors* be seamlessly integrated. Much effort have been devoted to develop the arbitration mechanism, but no satisfactory solution has been achieved yet. Ishikawa [9] presented a method based on the weighted sum of fuzzy rule base to fuse two *behaviors*, tracing planned path and avoiding obstacle. The weighting coefficients are determined by evaluating the obstacle-free distance (5 parameters each of which has 7 fuzzy sets), their time differences (7 fuzzy sets), STATE parameter (3 fuzzy sets) and SIDE parameter (3 fuzzy sets). As there are many situations to be handled, it is not easy to construct the rule base for the behavior arbitrator. Yen and Pfluger [10] proposed a fuzzy command fusion method which fused the path following *behavior* (PFB) and obstacle avoidance *behavior* (OAB) by the minimum operation of the desired direction from the PFB and the allowed direction from the OAB. They adopted the Centroid of the Largest Area method for defuzzification. This method fails when there are more than one largest area, and could cause vibration if the largest area alternates. Beom and Cho [11] introduced a method based on the potential field concept to fuse the obstacle avoidance *behavior* and the goal seeking *behavior*. However it suffers from the problem of potential local minimum.

In this paper, an new method for fusing the two independent and sometimes conflicting *behaviors*: obstacle avoidance and goal seeking is proposed. The balance between these two *behaviors* is achieved by combining the control actions from the goal seeker and the obstacle avoidor through evaluating the goal vector magnitude, the minimum distance detected by the ultrasonic sensors, and the distance to the obstacle in the direction of the goal vector. Having an environment evaluator operating in conjunction with them to tune the

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universe of discourse of the sensor space, the new navigation strategy has been verified to be efficient in an indoor virtual environment.

The remainder of this paper is organized as follows: In Section 2, the concept of behavior fusion is introduced. In Section 3, the vehicle model, the sensors arrangement and the navigation task are described. In Section 4, the fusion of the obstacle avoidance *behavior* and goal seeking *behavior* is presented. In Section 5, the performance of the behavior fusion approach is analyzed in a virtual indoor environment. Finally, the paper is concluded in Section 6 where future research directions are also outlined.

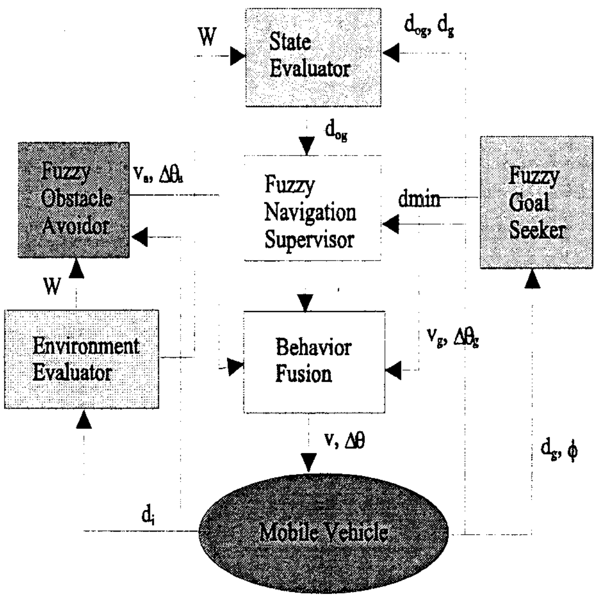

Figure 1: Diagram showing the behavior fusion strategy

2. CONCEPT OF BEHAVIOR FUSION

As depicted in Fig. 1, the aim of the proposed navigation strategy is to fuse two independent *behaviors*: obstacle avoidance and goal seeking in such a way that the goal seeking action does not cause the AMV to collide with an obstacle, and the obstacle avoidance action does not cause the AMV to deviate too much from eventually reaching the goal. Conceptually, the relationships of these two *behaviors* can be perceived as when there is an obstacle in the direction of the goal vector that is near to the AMV, then the obstacle avoidance action takes higher priority than the goal seeking action. Similarly, if the nearest obstacle to the AMV is far, then the goal seeking action takes priority. The question is how to determine this priority such that the eventual action is acceptable. In principle, two quantities must be known first. The first quantity describes how near is the nearest obstacle, and the second describes whether this obstacle is along the goal vector. If both quantities are large, then what it means is that the obstacles are far in the direction of the goal, and therefore, the goal seeking *behavior* is weighted very heavily. If both quantities are small, then it refers to the scenario that the AMV is very near an obstacle in the goal direction. In this case, collision avoidance action must take place. If any one of the two quantities is small and the other one is large, then the AMV should navigate with precaution. In other words, it should still weight more heavily on the obstacle avoidance *behavior*, less on the goal seeking *behavior*. It is based on this concept that the behavior fusion strategy was developed.,

3. VEHICLE & NAVIGATION MODEL

First, let's consider the basic vehicle and navigation model. The model of the vehicle used is a cylindrical mobile platform driven by two rear active wheels and a passive wheel. The radius of the mobile vehicle, R_v is assumed to be 20 *cm*. The vehicle is assumed to be equipped with a ring of 24 ultrasonic sensors as depicted in Fig. 2.

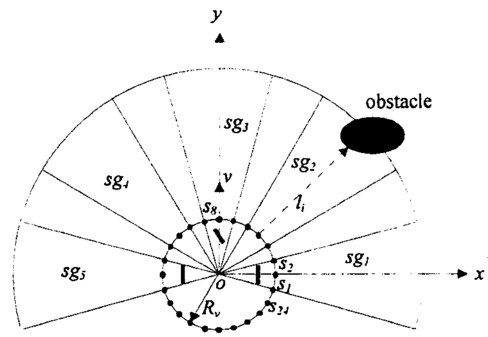

Figure 2: Mobile vehicle & ultrasonic sensors model

Each sensor, s_i for $i = 1,\cdots,24$ in the ring, gives a distance value to the obstacle, l_i, in its field of view, where $8cm \le l_i \le 400cm$ and the beam angle is 10°. For obstacle avoidance purposes, a subset of these sensors, s_i for $i = 1,\cdots,15$, are grouped into five groups and denoted by sg_i for $i = 1,\cdots,5$, where each group consists of 3 neighboring sensors. The remaining sensors are used by the FNS for measuring the minimum distance along the goal vector during navigation. With this sensor arrangement, the distance, d_i, measured by the i^{th} sensor group from the center of the vehicle to the obstacle is expressed as

$$d_i = R_v + \min(l_j \mid j = 3i-2, 3i-1, 3i); \text{ for } i = 1,\cdots,5 \cdot \qquad (1)$$

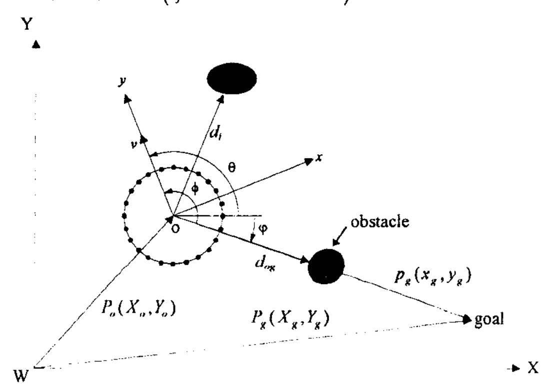

Figure 3: Diagram of the coordinate system

simulator was developed on the *SGI IRIX®* OS and the *OpenInventor®* platform. (*® Registered trademark of Silicon Graphics Inc.*). The simulation supports multiple view points and X-windows can be displayed simultaneously together with path statistics, and goal and start locations can be specified interactively via mouse or keyboard entry.

The world of the vehicle is an indoor floor space of offices and laboratories. Scene objects including tables, chairs, book shelves, human beings, robots and other mobile vehicles have been constructed according to their true dimensions and incorporated into the indoor environment. The simulator displays the top camera view of the complete virtual environment, which can be zoomed in and out; and an on-line 3D camera view generated by the camera modeled on top of the AMV. Typical views of the two viewpoints can be seen in Fig. 5(a) and Fig.5(b).

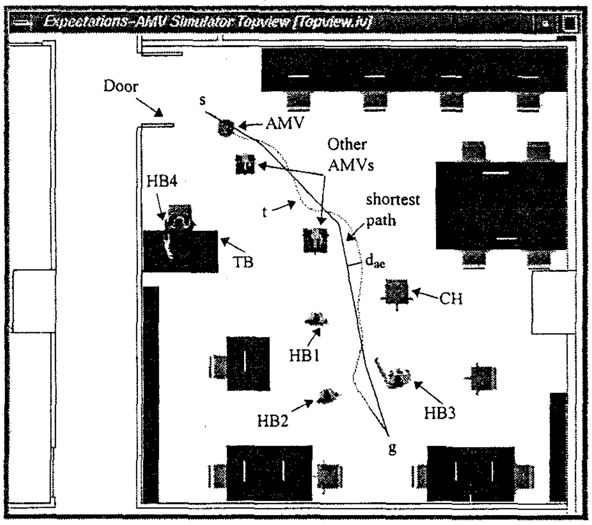

Figure 5(a): Top view of the AMV in action

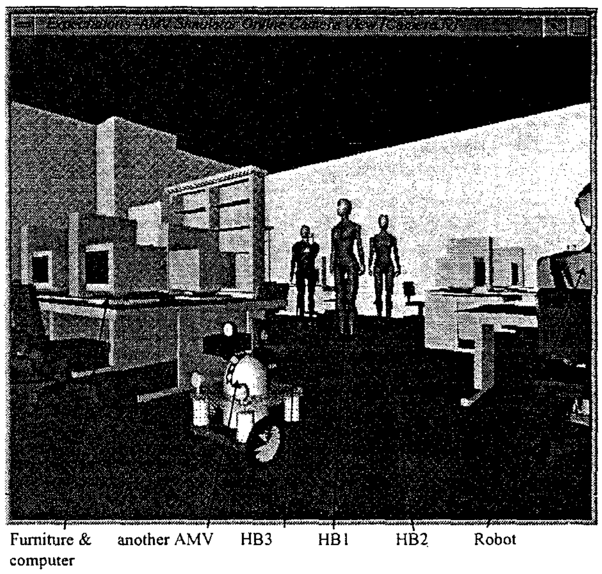

Figure 5(b): 3D perspective view of the AMV in action

For preliminary evaluation purpose, a navigation task from the start configuration **s** to the goal **g** as depicted in Fig. 5(a) was specified. The vehicle performed the trajectory **t** and navigated from **s** to **g** successfully. The transient of the velocity and the steering angle of the AMV when performing navigation task is shown in Fig. 6, where it can be observed that (1) the range of acceleration & deceleration is small when it passes by obstacles but large when the obstacles are in its path; (2) there is no abrupt change of velocity (±3 *cm/s*); (3) there is no abrupt change in the steering angle (±15°) either. These properties have obvious benefit for practical application when the vehicle's dynamics become an important consideration.

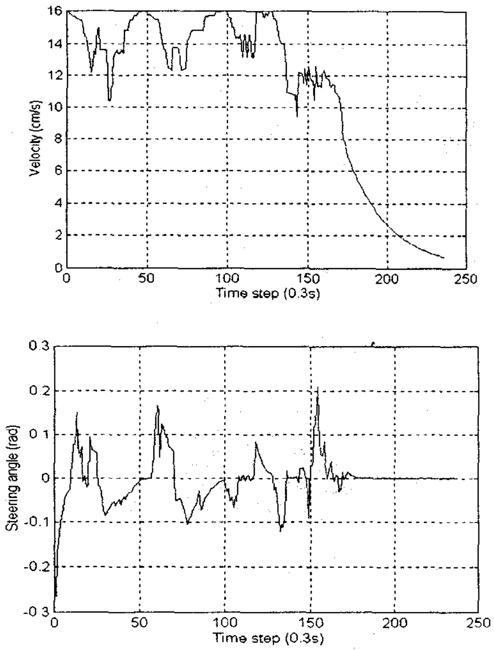

Figure 6: Transient velocity and steering angle

To further evaluate the path determined by the navigator, the Visibility Graph Method [16] was used to find the shortest path for the navigation task, which is depicted as the solid line in Fig. 5(a). At each time step, the deviation of the vehicle's position from the shortest path is denoted by d_{ae}. The length of the actual path and the shortest path are represented by p_a and p_e, respectively, and the relative error between the actual path length and the shortest path length, $(p_a-p_e)/p_e$ is denoted by E_r. On the same floor plan, five more navigation tasks with different number of obstacles were conducted and the errors are tabulated in Table 2. It can be observed that the paths derived from our navigator are reasonably close to the ideal path and the largest relative path error is only 6.1%. This is considered acceptable because the AMV has not explored the environment before, where the navigation was decided 'on-the-spot' when the obstacles were taken in account. In fact, it is believed that the errors would be larger without the behavior fusion module. Second, the relative path errors are proportional to the no. of obstacles present. This is to be

The coordinate systems and the control variables of the vehicle are depicted in Figure 3. The two coordinate systems are the world coordinate denoted by *XWY*, and the vehicle coordinate given by *xoy*. Based on these two coordinate systems, a navigation task is defined as navigating the vehicle from a start coordinate to its goal without colliding with the obstacles in between. Each navigation task is specified in the world coordinate, where the vehicle configuration is represented by $S=(X_o\ Y_o\ \theta)^T$, where (X_o, Y_o) represents the vehicle's center, and θ denotes the heading angle of the vehicle. Without considering the vehicle dynamics, we assume the control variables are its linear velocity v and the change in the heading angle (steering angle) , $\Delta\theta$.

In order to navigate the mobile vehicle to it's goal, it is assumed that the current configuration of the mobile vehicle is always known at each time step t. Therefore a navigation task consists of the following three steps: (1) obtain the environment information, d_i and $P_g(X_g, Y_g)$, and the vehicle's configuration S at each time step t; (2) determine the output variables $v(t)$ and $\Delta\theta(t)$; then update the vehicle's configuration; and (3) iterate this situation-action mapping process until the goal is achieved.

4. BEHAVIOR FUSION MODEL

From the fusion concept developed in Section 2, the behavior fusion model (BFM) encompasses the evaluation of the minimum obstacle distance, the minimum distance to the obstacle located along the relative goal vector, and the two actions decided by the fuzzy goal seeker (FGA) and the fuzzy obstacle avoidor (FOA). From [14], the FOA determines the action of the vehicle, v_a and $\Delta\theta_a$, based on the obstacle distance, d_i; while the FGS determines the vehicle's action v_g and $\Delta\theta_g$ based on the distance to the goal, d_g and the deviating angle from the goal, ϕ. When an obstacle is near the AMV and is in the direction of the goal, the actions recommended by these two *behaviors* are in conflict. To resolve this situation, two variables, d_{min} and d_{og}, are used as the input variables to the fuzzy navigation supervisor (FNS). Here, d_{min} stands for the minimum distance detected by the five ultrasonic sensor groups and is given by

$$d_{\min} = \min(d_i | i = 1,2,\cdots,5), \tag{2}$$

and d_{og} represents the minimum distance to the obstacle located along the relative goal vector $p_g(x_g, y_g)$. In order to detect this distance value, a sensor group on the AMV model is dynamically configured as s_i for $i = k-1, k, k+1$, where k is determined by

$$k = 2 + \mathrm{int}(\frac{12\varphi}{\pi}), \tag{3}$$

where $$\varphi = \tan^{-1}\left(\frac{Y_g - Y_o}{X_g - X_o}\right),$$

and int(•) refers to the rounding to the nearest integer. If i is zero or negative, then the modulo-24 of i is used instead. The distance, d_{og} detected by the sensor group is given by

$$d_{og} = R_v + \min(l_i | i = k-1, k, k+1). \tag{4}$$

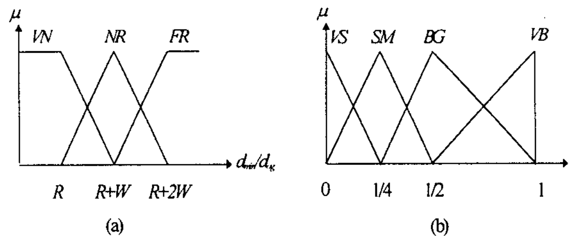

Figure 4: Membership functions of the input/output variables for the FNS

These two input variables are fuzzified in the FNS and fuzzy inference is made according to the membership functions depicted in Figure 4, where *R=28cm*. The membership functions of the input variables take exactly the same form as the FOA [14]. In accordance with the membership functions of the input variables, the rule base of the FNS consists of nine rules. They are given in Table 1. It should be noted that first, the *behavior* coefficient, η is very large when both variables are far, and very small when both variables are very near. Second, the fuzzification of d_{min} and d_{og} is determined by W, which tuned by the Environment Evaluator (EE). Finally, the crisp value of η is determined by the defuzzification [15]. In the case of an obstacle being too near to the goal, the State Evaluator (SE) sets $d_{og} = R_v + l_s$, where l_s is the shortest detectable distance; and if $\mu_{VN}(d_g)>0.5$ and $d_g<d_{og}$ then η=1. Eventually, the two *behaviors* are fused in the Behavior Fusion section where the command actions of the vehicle are determined by

$$\begin{cases} v = (1-\eta)v_a + \eta v_g \\ \Delta\theta = (1-\eta)\Delta\theta_a + \eta\Delta\theta_g \end{cases}. \tag{5}$$

d_{min} \ d_{og}	*VN*	*NR*	*FR*
VN	*VS*	*SM*	*SM*
NR	*SM*	*SM*	*BG*
FR	*SM*	*BG*	*VB*
	η		

Table 1: Fuzzy rules for the Navigation Supervisor

5. PERFORMANCE ANALYSIS

To evaluate the performance of the behavior fusion strategy in navigation, a fully integrated and interactive expected as the more obstacles in the direction of the goal location, more obstacle avoidance actions have to be taken which would caused more path errors. The larger degree of deviation is due to the EE which tends to take a larger clearance from the obstacles in order to avoid getting into local minima. Third, when there was no obstacles, the relative path error was 1.2%. This is due to the fact the AMV's initial heading angle was generally not set to point at the direction of the goal. As a result, the small error was due to the AMV turning and moving as the goal seeker took full control. If the vehicle's initial heading direction is aligned with the goal direction, the AMV will move along the shortest path giving zero error.

Using the identical set of obstacles and positioning, we have simulated the paths derived from the Environment Exploration Method (EEM) as depicted in Table 3. Comparing these results with our results, it is observed that their overall relative path errors are very similar with a difference of within 1%. The average and maximum path deviations of our method is slightly larger than the EEM results except for one case of which the EEM path has exceptionally large deviation because of a wrong turn. The total time elapsed in finding the path is slightly shorter for our method in all cases tested. However, the most important point is that the EEM navigation resulted in 1 collision each in the cases of 5-7 obstacles. This can be explained that as the EEM requires to explore in the actual operating environment and such complex environment as depicted in Fig. 5(a) is inherently difficult to fully explored, the rule base compiled by the EEM has far less rules than the rule based compiled by our training method [15] and therefore, caused collision as simulated.

6. CONCLUSION

We have presented a navigation strategy based on *behavior* fusion, which performs well in complex and unknown environments through a virtual world simulation. The principle of the navigation method is built on the fusion of the obstacle avoidance and goal seeking *behaviors* aided by an Environment Evaluator to tune the universe of discourse of the input sensor readings and enhance it's adaptability. Numerous simulation runs in an indoor virtual environment show that this navigation strategy is characterized by first, its ability to tackle an unknown environment without having to explore it beforehand or being supervised; second, its free of local minimum, i.e., no 'stuck-at' problems; third, it has smooth changes of velocity and steering angle, i.e., an advantage where vehicle dynamics are concerned; and fourth, its planned path is close to the shortest path, i.e., able to perform obstacle avoidance without sacrificing too much path efficiency.

In terms of future research directions, focus will be placed on first, to introduce the fusion of other type of *behaviors* to enhance the navigation capability; second, to construct a more accurate environment evaluator based on the obstacle density detected by a video camera; and third, to study the issues of dynamic obstacles of which trajectory prediction and estimation methods will be exploited.

Task	p_a/cm	p_e/cm	E_r	average d_{ae}	max. d_{ae}	time	no. of obstacles	no. of collision.
1	833.7	785.6	+6.1%	14.8cm	40.1cm	73.8s	7	0
2	795.0	759.8	+4.6%	9.8cm	33.8cm	70.2s	6	0
3	682.5	660.1	+3.4%	7.6cm	28.6cm	62.1s	5	0
4	584.3	573.0	+2.0%	4.3cm	13.2cm	54.6s	4	0
5	493.7	485.0	+1.8%	3.8cm	10.0cm	49.5s	2	0
6	424.1	422.9	+1.2%	3.1cm	8.5cm	45.6s	0	0

Table 2: Navigation results by the Behavior Fusion Method

Task	p_a/cm	p_e/cm	E_r	average d_{ae}	max. d_{ae}	time	no. of obstacles	no. of collision.
1	834.0	785.6	+6.2%	13.1cm	35.1cm	78.0s	7	1
2	794.0	759.8	+4.5%	25.9cm	95.5cm	73.2s	6	1
3	682.0	660.1	+3.3%	7.5cm	26.5cm	64.2s	5	1
4	584.0	573.0	+1.9%	4.1cm	12.9cm	56.4s	4	0
5	493.7	485.0	+1.8%	3.8cm	10.0cm	50.4s	2	0
6	424.1	422.9	+1.2%	3.1cm	8.5cm	45.6s	0	0

Table 3: Navigation results by the EEM

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