# Application of reactive multi-agent system to vehicle collision avoidance

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## Abstract

*Vehicle collision avoidance is a promising safety approach to new transportation systems, with innovative capabilities, such as obstacle detection, vehicle collision avoidance control strategy and adaptability to different obstacles. This paper presents a Reactive Multi-agent solution to the vehicle collision avoidance control problem with a linear configuration. In our case, vehicle collision avoidance is designed as a reactive multi-agent system in which agents interact with other agents and the obstacles situated in the environment by using physics inspired behaviors. Collision avoidance stability emerges as a global result of the individual interacted agents. Vehicle avoidance control strategy stems from calculating the trajectories of the vehicle based on the decision process of the reactive multi-agent system. Furthermore, the adaptation to different kind of obstacles is made by tuning model's physical parameters. In order to assert the transition from abstract to concrete, simulations experiments have been implemented and simulations results are analyzed.*

## 1. Introduction

Vehicle Collision Avoidance is a promising safety approach to new transportation systems, with innovative capabilities. It can be defined as a system for preventing collisions between a vehicle and other objects (which usually be called obstacles). Its main goal, when applied to civil cars, is to avoid the vehicle collision and increase the safety of vehicles in car travel. It can be divided into the two sub-problems: (i) Obstacle detection on the travelling path; (ii) Avoidance control strategy of the vehicle. Obstacle detection is to detect the obstacles on the travelling path of the cars. Traditionally, it can be realized by the signal sensors, the image processing or millimeter wave [1]-[3].The avoidance control strategy of the vehicle is to find the strategy to control the vehicle moving (the speed or direction) for avoiding the obstacles. In order to control the vehicle, some people use wireless communication networks and GPS device [4]-[7], some ones use the fuzzy logic-based controller [8]-[10], and others use the "Kalman filtering process" [11]. Sudha Arora and A.K.Mittal [12] introduce us a new method by introducing the "Priority Based Conflict Resolution" strategy to deal with the confliction of the AGVS (Automated Guided Vehicle Systems). Charles-Antoine Brunet [13] and Dong Eui CHANG [14] introduce an alternative approach for collision avoidance by introducing firstly the multi-agent systems: the former gives a multi-agent architecture for a driver model for Autonomous Road Vehicles and the latter illustrates a simple, decentralized control law for multiple vehicle agents by using gyroscopic forces and braking forces. As far as we known, reactive multi-agent approach has never been used as itself to be a decision process that is able to deal with the obstacle avoidance problem of the vehicle. Olivier Simonin and Franck Gechter [15] give us the methodology to design the reactive multi-agent systems. The main interests of the use of multi-agent systems especially reactive systems are the following intrinsic properties: adaptability, flexibility and reliability [16].

In this paper, we propose a vehicle collision avoidance solution based on the physics inspired reactive multi-agent system. It is able to deal with both the obstacle detection and vehicle avoidance control. The focus of other existing multi-agent models of collision avoidance commonly look on a vehicle as a single agent and then use different mathematical algorithms to acquire the control strategy of the collision avoidance. The difference of our model is the fact that we take into account a global

and dynamic point of view by introducing the reactive multi-agent system into a vehicle and finding the collision avoidance solution for the vehicle by global behavioral observation and calculating of the reactive agents.

This paper is structured as follows. The first part describes the multi-agent model used for the vehicle collision avoidance and the obstacle detection process. Second, the interaction model based on the Newtonian physics is defined. Third, the organization of decision agents was illustrated. Then the avoidance control strategy of vehicle is detailed. Finally, the simulations experiments and results analysis are exposed. The paper finishes with a conclusion and gives a presentation of our future work.

## 2. The Multi-agent Model

The multi-agent model formalized in this paper for vehicle collision avoidance is composed of four basic components: Environment, Agents, Interactions and Organization of the decision agents. In the model, we transformed the vehicle and its real world into the environment that the agents will face with. In this environment, each reactive agent is characterized by a set of attributes such as the mass, position and the speed. Each agent is also assigned to a specific role that can be characterized as a set of interaction behaviors. In order to realize the obstacle avoidance scenario, two main agent roles are defined: the *decision agent* role and the *obstacle agent* role. When the vehicle moves, the obstacle that the vehicle faced with is detected by the sensors installed on the vehicle and then to be added as an obstacle agent into the environment. The interactions between the decision agents and the obstacle agents are based on the physics inspired model according to the decision agent's perception range. The avoidance control strategy for the vehicle is finally stems from the observation of the decision agents' organization and calculating the trajectories of the vehicle. The calculating of the trajectories of the vehicle is according to the decision process from the decision agents that interacted with other decision agents and the obstacle agents situated in the environment. Moreover, the parameters of the multi-agent model can be configured manually or empirically in order to adapt the different situations. We will illustrate them in the following parts in detail.

### 2.1 Environment

The environment defined in the multi-agent model is the perception length, range or images detected by the sensors installed on the vehicle. It is the link between the real world perceived by vehicle sensors and the decision agent world which goal is to make decisions for the vehicle. The environment has both static and dynamic attributes. The static attribute of the environment is named as *Topology*, it represents the static view of the environment. It commonly includes the perception length, range or images that sensors could detect. In the model, parameter $L$ represents the length that the sensors could detect, parameter $A$ represents the range that the sensors could detect and parameter $C$ represents the storage images of the sensors. We could acquire the total information of the environment by using the fusion approach [15] of above data from the different sensors on the vehicle; The dynamic attribute of the environment is named as *Dynamics*, it represents the topology of the environment on its dynamic. It includes two dynamical changes [15] of the obstacles in front of the vehicle: the *emergence* of obstacles and the *disappearance* of obstacles. These two dynamic changes are continuously detected by the sensors installed on the vehicle as a loop.

### 2.2 Agents

In the environment, two reactive agent roles are defined. One agent role is named as *decision agent*, it represents the reactive agent in the environment which goal is to make decisions for the vehicle; the other agent role is named as *obstacle agent*, it represents the real obstacles emerged or disappeared in the environment that the vehicle need to avoid. Their definitions are to be realized the obstacle avoidance scenario of the vehicle according to the decision process from the decision agents that interacted with other decision agents and the obstacle agents. Each agent role is characterized by some attributes parameters in our model.

#### 2.2.1 Decision Agent
The *decision agent* role has the attributes parameters *m, s, v, a, r, R, IE* (seen in **Table 1**).

#### 2.2.2 Obstacle Agent
The *obstacle agent* role can be regarded as an *agent* without some attributes or with a few attributes value changed. It has the attributes parameters *M, S, V, A, SI, OIE, Fix* (seen in the **Table 2**).

#### 2.2.3 Obstacle Detection
The obstacle detection process for the vehicle is directly related with the sensors installed on the vehicle. The sensors installed on the vehicle will continuously detect the real world of the vehicle to find whether an

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**Table 1. Attributes of the Decision Agent**

| Attributes | Description |
|---|---|
| $m$ | mass of a decision agent |
| $s$ | position of a decision agent |
| $v$ | speed of a decision agent |
| $a$ | acceleration of a decision agent |
| $r$ | Perception range of a decision agent to another (seen in **Figure 1**) |
| $R$ | Perception range of a decision agent to an obstacle agent (seen in **Figure 1**) |
| $IE$ | the internal energy of a decision agent |

**Table 2. Attributes of the Obstacle Agent**

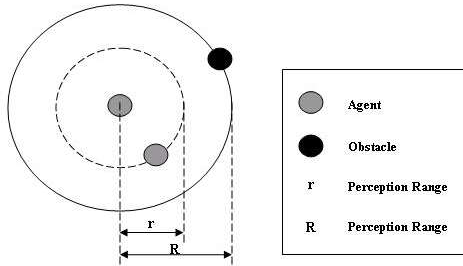| Attributes | Description |
|---|---|
| $M$ | mass of an obstacle agent |
| $S$ | position of an obstacle agent |
| $V$ | speed of an obstacle agent |
| $A$ | acceleration of an obstacle agent |
| $SI$ | size of an obstacle agent |
| $OIE$ | the internal energy of an obstacle agent |
| $Fix$ | the Boolean value to indicate obstacle agent is fixed or not |



**Figure 1. Perception range of a Decision Agent**

obstacle emerged on the traveling path. When the sensors capture an obstacle, they will send the position, size, speed and other information of the obstacle to the reactive multi-agent system and therefore an obstacle agent will be added into the environment according to the position and the size of the real obstacle.

## 3. Interaction Model

We assumed that the interaction behaviors between the decision agents and between the decision agents and the obstacle agents are followed the Newton's law of gravitation according to the decision agent's perception range. We defined them both as the repulsion behaviors in order to accord with the obstacle avoidance scenario. Therefore, there are two kinds of repulsion interactions emerged in the environment: *Decision Agent- Decision Agent* Interaction (*A - A* Interaction) and *Decision Agent-Obstacle Agent* Interaction (*A-O* Interaction).

### 3.1 A-A Interaction

A repulsion force emerged between two Decision Agents as the result of the A-A Interaction. This repulsion force takes action when two decision agents are closed to less than the perception range (repulsion range) $r$ of an agent (seen in **Figure 2**). In the interaction model, we use the following physical force equation (1) to represent this kind of interaction:

$$\vec{F}_{AiAj} = \alpha m_i m_j \frac{\overrightarrow{A_i A_j}}{d^3} = -\alpha m^2 \frac{\overrightarrow{A_i A_j}}{\left\|\overrightarrow{A_i A_j}\right\|^3}, (d \le r) \quad (1)$$

$\vec{F}_{AiAj}$ represents the repulsion force vector between the decision agent $A_i$ and $A_j$, $\alpha$ (alpha) is defined by the gravitational constant between two decision agents, $m_i$, $m_j$ are the masses of the two decision agents $A_i$ and $A_j$, they are commonly the same value because the agents distribution are homogeneous (with same attributes), $d = \left\|\overrightarrow{A_i A_j}\right\|$ is the distance between the decision agent $A_i$ and $A_j$, $r$ is perception range(repulsion force range) to another decision agent $A_j$ of the decision agent $A_i$.
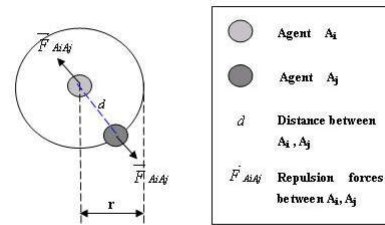


**Figure 2. Repulsion forces between two Decision Agents**

### 3.2 A-O Interaction

A repulsion force emerged between a Decision A*gent* and an Obstacle Agent as the result of the A-O Interaction when an obstacle agent is in the perception range $R$ of a decision agent (seen in **Figure 3**). In the interaction model, we use the following physical force equation (2) to represent this kind of interaction:

$$\vec{F}_{AiOk} = \beta m_i M_k \frac{\overrightarrow{A_i O_k}}{D^3} = -\beta m_i M_k \frac{\overrightarrow{A_i O_k}}{\left\|\overrightarrow{A_i O_k}\right\|^3}, (D \le R) \quad (2)$$

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$\vec{F}_{AiOk}$ represents the repulsion force vector between the decision agent $A_i$ and obstacle agent $O_k$. $\beta$ (beta) is defined by the gravitational constant between the decision Agent and the obstacle Agent, $m_i$ is the mass of the decision agent $A_i$ and $M_k$ is the mass of the obstacle agent $O_k$, it is proportional to the size of the obstacle agent $O_k$. $D = \left\| \overrightarrow{A_iO_k} \right\|$ is the distance between the decision agent $A_i$ and the obstacle agent $O_k$, $R$ is the perception range (repulsion force range) to an obstacle agent $O_k$ of the decision agent $A_i$.
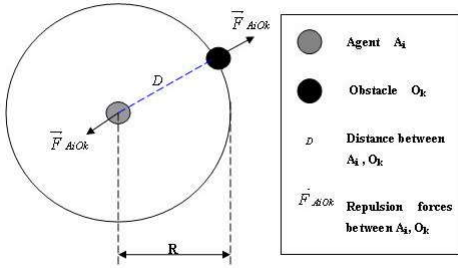


**Figure 3. Repulsion forces between a Decision Agent and an Obstacle Agent**

## 3.3 Interactions behaviors in the Environment

Besides the above $\vec{F}_{AiAj}$ and $\vec{F}_{AiOk}$ interaction forces of the decision agent $Ai$ in the environment, the Fluid friction force $\vec{F}_{f_i}$ has also been added to the interaction forces of the decision agent $A_i$ taking into account the dynamics and the real world. It is also used to avoid the perpetual movement of the decision agents. The parameter $\lambda$ is the friction factor, the Fluid friction force $\vec{F}_{f_i}$ is as the following equation (3) ($\vec{V}_{Ai}$ is the speed vector of the decision agent $A_i$ ) :

$$\overrightarrow{F_{f_i}} = \lambda \overrightarrow{V_{Ai}} \quad (3)$$

Therefore, there are three kinds of interaction forces among the decision agents and obstacle agents in our interaction Model:

- *Agent-Agent Repulsion Force* $\vec{F}_{AiAj}$
- *Agent-Obstacle Repulsion Force* $\vec{F}_{AiOk}$
- *Fluid friction force* $\vec{F}_{f_i}$

By using above interaction forces defined in the multi-agent model, we could calculate the acceleration value

$\vec{a}_i$ of a decision agent $Ai$ with the following difference equation (4) according to the Newton's law of motion:

$$m_i \vec{a}_i = \sum_j \overrightarrow{F_{AiAj}} + \sum_k \overrightarrow{F_{AiOk}} - \overrightarrow{F_{f_i}}$$

$$= \alpha \sum_{j=1}^n m_i m_j \frac{\overrightarrow{A_iA_j}}{d^3} + \beta \sum_{k=1}^q m_i M_k \frac{\overrightarrow{A_iO_k}}{D^3} - \lambda \overrightarrow{V_{A_i}} \quad (4)$$

$(i, j \in [1, n], k \in [1, q]; \alpha, \beta, \lambda \in [0,1]; d \leq r; D \leq R)$

Here $\sum_j \vec{F}_{AiAj}$ represents the vector sum of the repulsion forces of the decision agent $A_i$ and other decision agents, the $\sum_k \overrightarrow{F_{A_iOk}}$ represents the vector sum of the repulsion forces of the decision agent $A_i$ and the obstacle agents it perceived. The indicator $\alpha$ (alpha) and $\beta$ (beta) are the two gravitational constants to these two interactions of the decision agent $A_i$, $d = \left\| \overrightarrow{A_iA_j} \right\|$ and $D = \left\| \overrightarrow{A_iO_k} \right\|$ are respectively the distances between decision agent $A_i$-$A_j$ and the distance between decision agent $A_i$ and obstacle agent $O_k$.

Because the decision agents are homogeneous (with the same attributes), and their masses are always the same value. Therefore, we can simplify the equation (4) to the following equation (5):

$$m\vec{a}_i = \sum_j \overrightarrow{F_{A_iA_j}} + \sum_k \overrightarrow{F_{A_iO_k}} - \overrightarrow{F_{f_i}}$$

$$= \alpha m^2 \sum_{j=1}^n \frac{\overrightarrow{A_iA_j}}{d^3} + \beta m \sum_{k=1}^q M_k \frac{\overrightarrow{A_iO_k}}{D^3} - \lambda \overrightarrow{V_{A_i}} \quad (5)$$

$(i, j \in [1, n], k \in [1, q]; \alpha, \beta, \lambda \in [0,1]; d \leq r; D \leq R)$

By discrete integration to equation (5), we can calculate the new acceleration, velocity, position and energy of the decision agent $Ai$ after interactions in the environment according to the Newton's law of motion. Thus all the attributes parameters of agents defined in **Table 1** and **Table 2** could also be computed thanks to the equation (5).

## 4. Organization of the Decision Agents

The result of the interaction behaviors between the decision agents and between the decision agents and the obstacle agents situated in the environment is that the decision agents will finally form a self organization to react to the obstacle agents in the environment (seen in **Figure 4**). In **Figure 4**, there are three fixed obstacle agents (three points in the center of the figure) in the environment and the decision agents (the most points surround the three points) form a self organization to

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react to the three fixed obstacle agents. The emerged short straight line in the south of the **Figure 4** represents the mean position changes of the all the decision agents interacted in the environment as the time changed. Therefore, we can acquire the mean position change vector of the decision agents in each time step with the continuous observation of the decision agents' organization and make it as the foundation of decision process to control the vehicle.
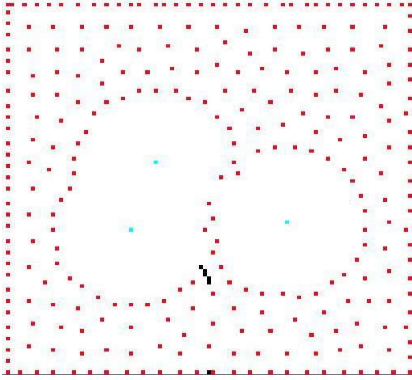


**Figure 4. The organization of the Decision Agents (three fixed obstacle agents)**

## 5. Avoidance Control Strategy to the vehicle

The avoidance control strategy to the vehicle is shown in **Figure 5**. It is a continuous loop when the vehicle is moving.
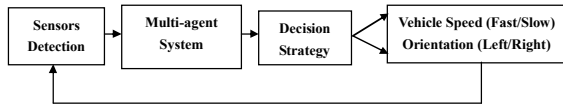


**Figure 5. Reactive Multi-agent avoidance control strategy to the vehicle**

The reactive multi-agent system firstly acquires the obstacles information from the sensors installed on the vehicle which to be used to detect the real world. Then the obstacle agents will be added by the reactive multi-agent system into the environment according to the positions and sizes of the real obstacles. The avoidance decision strategy for the vehicle will finally be acquired by the timely observations of the organization of the decision agents and calculating the trajectories of the vehicle. The calculating is according to the decision process from the decision agents that interacted with

other decision agents and the obstacle agents situated in the environment. In this paper, we use the mean position vector of the decision agents that have interacted in the environment as the basic physical vector to calculate the trajectories of the vehicle, seen in equation (6).

$$\overrightarrow{S_{mean}(t)} = \frac{1}{n} \sum_{i=1}^{n} \overrightarrow{S_{Ai}(t)} \quad (6)$$

Here the position vector $\overrightarrow{S_{Ai}(t)}$ is the position vector of the decision agent $A_i$ (i=1..n) in time step $t(t=1..m)$ in the environment, it can be easily calculated by the above equation (5). The position vector $\overrightarrow{S_{mean}}(t)$ is the current mean position of all the agents that have interacted in the environment in time step t. By calculating the position vector difference $\overrightarrow{\Delta S_{mean}}(t)$ between the current time t step $\overrightarrow{S_{mean}}(t)$ (t=1…m) and the time t-1 step $\overrightarrow{S_{mean}}(t-1)$, we can acquire the vehicle reference speed difference $\overrightarrow{\Delta V_{mean}}(t)$ by simplified discrete differential to $\overrightarrow{\Delta S_{mean}}(t)$. Therefore, we can see that the reference speed difference vector $\overrightarrow{\Delta V_{mean}}(t)$ is given by the decision agents interacted in the environment and inspired by the physics inspired interaction model. It is then used as a decision support vector which can automatically change the speed, direction and position of the vehicle. The automatic change of the vehicle speed and its position from the decision process of all the decision agents that interacted in the environment are shown in equation (7) and equation (8).

$$\overrightarrow{V}(t) = \overrightarrow{V}(t-1) + \Delta \overrightarrow{V}_{mean}(t) \quad (7)$$

Here $\overrightarrow{V}(t-1)$ is the vehicle speed vector in time t-1 step, $\Delta \overrightarrow{V}_{mean}(t)$ is the current reference speed difference vector from the agents, $\overrightarrow{V}(t)$ is the new speed vector of vehicle in the current time step t.

$$\overrightarrow{s}(t) = \overrightarrow{s}(t-1) + \overrightarrow{\Delta s}_{mean}(t) \quad (8)$$

Here $\overrightarrow{s}(t-1)$ is the vehicle position vector in time t-1 step, $\Delta \overrightarrow{s}_{mean}(t)$ is the current reference position difference vector from the agents, $\overrightarrow{s}(t)$ is the new position vector of vehicle in the current time step t.

By using the equation (7) and equation (8), the reactive multi-agent system could timely change the speed and the orientation of the vehicle in order to realize automatically the collision avoidance to the obstacles of

the vehicle. It is also easy to acquire the collision avoidance trajectories of the vehicle by above calculations.

Therefore, we can see that the avoidance control strategy stems from a composition of the vehicle itself and the influences computed by the decision agents.

## 6. Simulation results

### 6.1 Simulations environment

The physical inspiration multi-agent model described in the previous section has been implemented based on the multi-agent platform[1] proposed by *J.Ferber* and *O. Guknecht*. This simulation is used to validate some characteristics of our multi-agent model. When the simulation program is running, the connecting component can automatically connect to the sensors installed on the vehicle by the TCP/IP interface (because the reactive multi-agent system commonly running on another computer that remote to the intelligent vehicle) in order to acquire the information such as the position, size, speed and mass (commonly proportional to the size of the obstacle) of the obstacles in front of the vehicle. Then the reactive multi-agent system will automatically calculates the speed vector and position vector of the vehicle in each time step according to the initial position and initial speed of the vehicle and finally finds the vehicle collision avoidance trajectory to control the speed and the orientation of vehicle.

### 6.2 Simulations results analysis

When the parameters of the multi-agent model are empirically configured by the following: the decision agent mass $m=50$ (which is equal to 1000kg in reality), the obstacle agent mass $M=50$ (which is equal to 1000kg in reality), the repulsion factor $\alpha=\beta=0.2$, *the friction factor $\lambda=0.07$,* the perception range of decision agents $r=10mm$ (which is equal to 25m in reality)*,* the perception range to obstacle agents $R=20mm$ (which is equal to 50m in reality), the simulation environment is defined by *100mm\*100mm* rectangle scope (which is equal to the 250m\*250m space in reality)*, the size of the obstacle agent SI=1mm* (which is equal to the 2.5m length in reality). We acquired the following simulations results in the situation of the fixed obstacles from **Figure 6** to **Figure 10**.

**Figure 6** illustrates the avoidance trajectory of vehicle when there are 300 decision agents and 1 fixed
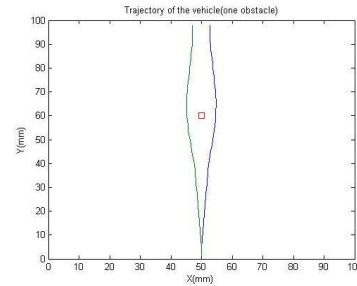
[1] Madkit5，http://www.madkit.org

**Figure 6. The trajectory of vehicle (one fixed obstacle)**

obstacle agent in the environment. Just like an ant to find the shortest path for the food, when the vehicle faced one obstacle in front of it, there are two equal possibilities for the vehicle to choose from the left side or right side to avoid the obstacle, so there are two symmetrical trajectories emerged in the simulation process.
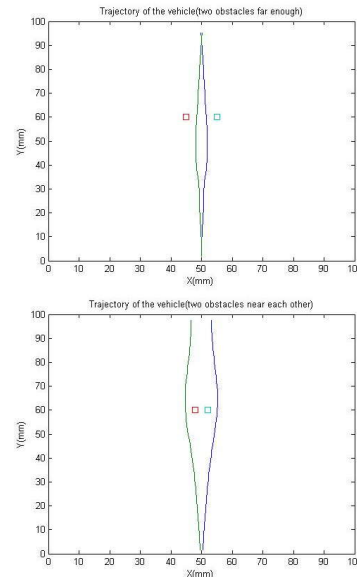


**Figure 7. The trajectory of vehicle (two fixed obstacles)**

**Figure 7** illustrates the avoidance trajectory of the vehicle when there are 300 decision agents and 2 fixed obstacle agents in the environment. We can see the vehicle will form the different trajectory if the distance between two obstacle agents is different. The above one illustrates the trajectories of the vehicle when two obstacle are far enough (the distance between them is bigger than the size of the vehicle 2.5m length to pass through). It is nearly a straight line while not is because some interaction influences by the two obstacle agents. The lower one illustrates the trajectories of the vehicle when the two obstacles are near enough (the distance is

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smaller than the size of the vehicle 2.5m to pass through).The calculation process of the trajectory can be seen in equation (7) and equation (8).
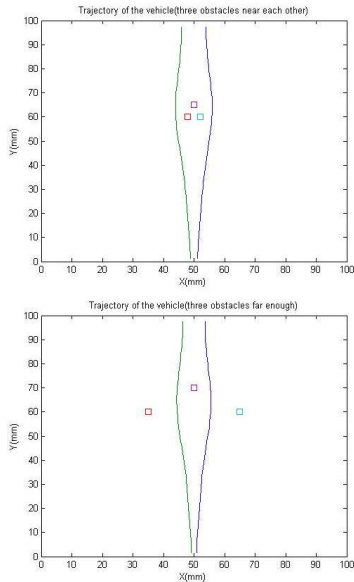


**Figure 8. The trajectory of vehicle (three fixed obstacles)**

**Figure 8** illustrates the avoidance trajectory of the vehicle when there are 300 decision agents and 3 fixed obstacle agents in the environment. We can see the vehicle will form the different trajectory if the distances among three obstacles are different. The above one illustrates the trajectories of the vehicle when the three obstacles are near enough (the distances among them are smaller than the size of the vehicle 2.5m to pass through). The lower one illustrates the trajectories of the vehicle when the distances between any two obstacles are far enough (bigger than the size of the vehicle 2.5m to pass through).
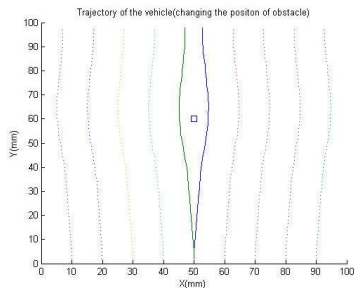


**Figure 9. The trajectory of vehicle (changing the initial position of the vehicle)**

**Figure 9** illustrates the different avoidance trajectories when the vehicle dynamically changes its initial position (it changes its position along the X coordinate by 10mm difference in the simulation environment, which is equal to 25m in reality). There are 300 decision agents and 1 fixed obstacle agent in the environment. We can see the vehicle will form the different trajectories if its initial position (comparing to the position change of the obstacle) is different. The middle ones illustrate the trajectories of the vehicle when the obstacle is just in front of it. The other ones show the trajectories of the vehicle when the initial position of the vehicle is moving along the left/right directions. We can see the farther of the distance between the obstacle and the vehicle the more straight-line liked of the trajectory of the vehicle because the vehicle needn't to avoid the obstacle. On the contrary, the trajectory is more bended because the influence of the obstacle.
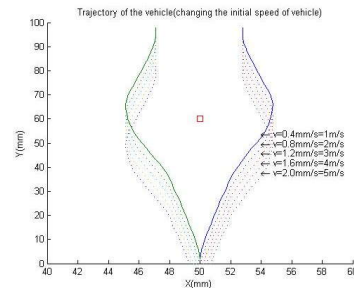


**Figure 10. The trajectory of vehicle (changing the initial speed of the vehicle)**

**Figure 10** illustrates the vehicle avoidance trajectories when the vehicle increases its initial speed vector along the Y coordinate by 0.4mm/s (which is equal to 1m/s in reality, the maximum speed is 2mm/s=5m/s in reality). There are 300 decision agents and 1 fixed obstacle agent in the environment. We can see from the **Figure 10** the different trajectories if the initial speed of vehicle is different. The middle ones illustrate the trajectories of the vehicle at the speed 0.4mm/s (1m/s), the other ones show the trajectories of the vehicle when its speed changed from 0.8mm/s (2m/s) to maximum 2mm/s (5m/s). We can see from the Figure that the faster the speed of the vehicle, the more bended of the trajectories of the vehicle will be because the vehicle will change its direction earlier to avoid the obstacle. On the contrary, the trajectories are less bended and the vehicle will change its direction later to avoid the obstacle.

In order to find the best solution to the collision avoidance control with different kinds of obstacles for the vehicle, we could also manually configure the parameters of our multi-agent model in the simulation environment.

# 7. Conclusion

This paper is aimed to present a reactive multi-agent approach to the vehicle collision avoidance problem. In this paper, we propose a multi-agent model, in which we change the vehicle and its real world into the environment that the agents faced with. A reactive multi-agent system is defined in the environment which includes two main reactive agent roles – the *decision agent* and the *obstacle agent*. The agents' interactions behaviors are inspired by Newtonian physics. For each agent interacted in the environment, interactions are only limited to a perception scope, while it can realize the decision process by the continuously global behavioral observation of the decision agents' organization. The collision avoidance stability emerges as a global result of the individual interacted decision agents. The avoidance control strategy for the vehicle stems finally from calculating the trajectories of the vehicle based on the decision process of the reactive multi-agent system. The simulations results illustrate the essential characteristics of this kind of solution: *adaptability* (tuning the model's physical parameters), *flexibility* (changing the number of the obstacles) *and reliability* (changing the position and the speed of the vehicle). However, there are some problems to be considered in the future such as how to deal with the moving obstacles and how to optimize the model parameters to acquire the better adaptation to different kind of obstacles. Therefore we are now running into the further research on the following two points: (1) Finding the vehicle collision avoidance strategy in order to cope with the moving obstacles; (2) Finding the optimization configuration parameters of the multi-agent model in order to adapt to different kinds of obstacles.

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