A PREDICTIVE CONTROL SOLUTION FOR CONTINGENCY MOTION PLANNING FOR AUTONOMOUS VEHICLE

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***Abstract*— With a model-based prediction control approach to generate optimal trajectory and avoid collision in many situations that cannot perform emergency braking, this paper proposes a solution to optimal path planning and safety assurance to avoid collision for autonomous vehicle by identifying the possible motion trajectories of the vehicles ahead when participating in traffic. The safety factor to avoid collision is performed in each motion phase of the vehicle, with the development of a nonlinear constraint between the brake and the steering angle for the vehicle's contingency motion planning. The efficiency of this solution is evaluated through assumpted simulations with different scenarios, then there are orientations toward applied research on the problem of autonomous vehicles in reality.**

Keywords—Autonomous vehicle, Model Preditive Control, path planning, motion planning, intelligent transportation systems.

I. INTRODUCTION

Many researches on autonomous vehicles problems have been carried out in recent years based on basic components such as localization system, environmental perception, planning and controlling [3,13,17]. In these components, the motion planning problem is an important function to determine the motion process of the vehicle, which provides the target destination of the vehicle by using information obtained from the environment and localization system. Therefore, the components in the planning consider not only the elements of the vehicle but also the changes of the environment through the perception data obtained in the system to ensure the reliability and security when participating in traffic.

The strong development in driving assistance systems has significantly reduced the risk of rear-end collisions on the road. However, in practice there are cases when the speed is large, the remaining processing time is too short to perform emergency braking for obstacle avoidance. With these situations, in order for the motion planning to be safe, changing the motion process by the contingency motion plans is performed to avoid possible collisions. Challenges to this problem might be: The presence of moving obstacles, the combined effect between the internal dynamics and the vehicle structure, the planning cycle and the response time do not match.

To solve this problem, if a motion trajectory of the autonomous vehicle is generated based on the possible trajectories of other vehicles, safety is not guaranteed because conflicts can happen when determining trajectory planned according among different objects in traffic. Therefore, the solution to building a contingency trajectory to meet safety in all traffic situations is the key idea of this paper, the contingency trajectory created has to pay attention to possible trajectories in other transportation means. Then, at each stage, the solving process will maintain the computational operations the possible actions of the vehicles in traffic. In the case if the contingency trajectory is not found feasible in an emergency situation, activation of the emergency brake system is applied until a new feasible trajectory is found.

Motion planning solution can be applied to a variety of approaches such as discrete-time planning with a grid-based approach [14], basic motion method [4], RRT trees [10,11] and PRM method [[18]; Or planning in continuous space with optimal control method, controlling predictive model [9,16] or elastic bands [15].

To ensure safety and facilitate for motion planning in complex environmental conditions is a major problem due to the uncertainty of many possible trajectories generated by other vehicles. However, some studies have aimed at the safety of motion plans by computing and setting up emergency manoeuvre, and some prior conditions such as communication between vehicles and determined future trajectories [7] during the process of building trajectory for the motion planning.

In this paper, we propose a solution for the establishment of a contingency plan for the safety of the autonomous vehicle by building an optimal path based on the assessment of the mobility of other vehicles in a certain period of time, then with each motion trajectory will compute the adaptation emergency operations.

The next section will introduce the basic principles for building motion plans and related algorithms, thereby motion planning solution is proposed with model-based predictive control approach. The experimental section is followed and in the conclusion section the future research directions for the autonomous vehicle are suggested.

II. BUILDING MOTION PLANING SOLUTION FOR AUTONOMOUS VEHICLES

In the structured road, the path system is defined by adjacent lanes of arbitrary shape and curvature. In this article, to be convenient for performing, we assume and consider the i^{th} ($lane_i$) is a path defined by the left boundary (B_{Li}) and the right boundary ($lane_i$). Each such path is defined as a polyline and is a combination of all lanes at a given time interval ($lane(s) = \bigcup_i lane_i$). At the same time, we know the joint between the adjacent lanes.

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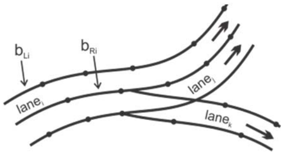

Figure 1. Road system model

In the overall coordinate system, each vehicle and other objects are represented by its position (S_x, S_y) in the boundary of the lane, the direction θ_r, the distance symbol to the vehicle d_r and the reference arc length s_r represents the state of the system, $K_r(S_r)$ is the curvature parameter of the reference curve (Fig. 2).

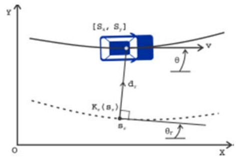

Figure 2. Vehicle and reference curve model

II.1 Building predictive models

The nature of the Model Predictive Control (MPC) is to use the object model to predict the output of the object at future times (also known as output signal predictive domain) and to compute the control signal sequencing based on the minimum objective function, and also uses the long-range strategy, i.e. at each time only the first control signal in the series is put into use, limiting prediction move to the future after each computation.

However, the proposed algorithms for the predictive model [12] will not directly introduce trajectories into the vehicle's motion system, which is a necessary advantage when using the predictive model. This has facilitated the optimization of the predictive model as a long-term cycle for the selection of options to ensure that there is no danger to the stability of the whole system. In addition, the predictive model can be designed to combine with the relevant binding properties of the vehicle to facilitate the optimization of the fast process. With such an idea, we use the following predictive model as the basis for the research issue (Fig. 2).

The first part of the predictive model is proposed as follows:

$$\dot{S}_x = v\cos\theta \tag{1}$$

$$\dot{S}_y = v\sin\theta \tag{2}$$

$$\dot{\theta} = \frac{\vartheta}{l\left[1+\left[\frac{v}{v_{ch}}\right]^2\right]}\,\delta \tag{3}$$

$$\dot{\delta} = u_1 \tag{4}$$

$$\dot{v} = u_2 \tag{5}$$

Where: the notation $\dot{x}$ represents the first derivative of x; S_x, S_y and v are the reference position of the vehicle and the corresponding velocity; θ indicates the movement direction of the vehicle; δ is the steering angle of the wheel; velocity and time derivative of the vehicle velocity act as inputs u_1 and u_2 of the system.

Equation (3) is a linear model performing stable state [5], whose only parameter is the characteristic velocity v_{ch} is computated as:

$$v_{ch} = \sqrt{\frac{l^2 c_f c_r}{m[c_r l_r - c_f l_f]}} \tag{6}$$

Where: m is the mass of the vehicle; c_r and c_f are the anti-rotation of the rear and front wheels (this hardness is usually measured at the wheel slip angle by 0); l_r and l_f are the distances between the rear axle and the front axle with the center of gravity ($l = l_r + l_f$: the length of the vehicle).

This model has the following advantages: There is no singularity at v = 0 and it allows the brake to stop completely, and the dynamic system is not rigid, so the simulation time step of the decoder has quite large size, so the optimal speed of the model increases.

The value of the reference curve defined here is the boundary of the lane

$$\dot{d}_r = v\sin(\theta - \theta_r) \tag{7}$$

$$\dot{\theta}_r = v\,\frac{\cos(\theta-\theta_r)}{1-d_r K_r(S_r)}\,K_r(S_r) \tag{8}$$

$$\dot{S}_r = v\,\frac{\cos(\theta-\theta_r)}{1-d_r K_r(S_r)} \tag{9}$$

Since the trajectory of a vehicle can deviate from the standard road during the process of avoiding obstacle, this model cannot be transformed into linear activity. For arbitrary shaped reference curves, this transitional simulation method is more effective than performing geometric projections.

In order to compute the drawbacks of the traction wheel, the driving system of the vehicle as well as the regulating direction when overcoming obstacle, some constraints need to be set when building the trajectory. The constraints set on state and input must meet the following conditions:

$$v \in [0, v_{max}] \tag{10}$$

$$u_2 \in [a_{min}, a_{max}] \tag{11}$$

$$u_1 \in [\dot{\delta}_{min}, \dot{\delta}_{max}] \tag{12}$$

$$\delta \in [\delta_{min}, \delta_{max}] \tag{13}$$

$$d_r \in [d_{r,min}, d_{r,max}] \tag{14}$$

$$(S_y, S_y) \in lanes \tag{15}$$

Where: (10) and (11) are the physical constraints on the values of velocity and acceleration; (12) and (13) are constraints on the power steering integrated system, these constraints support the generation a more variable motion trajectory of vehicle; (14) and (15) are constraints on lane limits, which is intended to help the vehicle out of the lane boundary; Parameters for maximum velocity v_{max}, acceleration a_{min} and a_{max}, steering angle δ_{min} and δ_{max} are predetermined.

In order to control the transom (also known as the transverse), the total friction between the tires and the road surface must not exceed a maximum value, which results the overall force of the vehicle also restricted similarly. Thus, in order to accommodate the vector acceleration the vehicle vector $[a_n, a_t]^T = [v\dot{\theta}, u_2]^T$ must be in the center ellipse defined by half of the c_n and c_t axis (Fig. 3), hence:

$$\left[\frac{a_t}{c_t}\right]^2 + \left[\frac{a_n}{c_n}\right]^2 \leq 1 \tag{16}$$

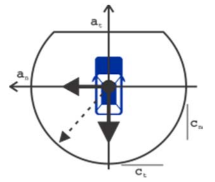

Figure 3. The elliptical contact created by the combination of horizontal and vertical traction

For handling the cases with obstacles, although the cost computation for adjacent regions to ensure convergence is not simple, this problem still brings more advantages than strict constraints to prevent collisions, in which the distance to other objects can be used as slack variables. However, instead of solving the optimal convergence problem on the left or right side of the obstacle, in this case it is necessary to introduce the constraints and regulations that are the constraints in front of the vehicle. Therefore, it is necessary to introduce additional variables $\xi_m(r), m \in 1 \ldots M$ used to denote the vector from the center of the obstacles to the location of the vehicle. Also, the predictive time $r \in T_{hor}$ needs dertemining.

$$t_{d_{min,m}} \coloneqq \underset{t}{\operatorname{argmin}}\, d_m(r) \tag{17}$$

At this point, the distance from the obstacle m to the vehicle of the smallest value $d_m(r)$ with $n(r)$ is the normal vector to the motion trajectory $\left[S_x(r), S_y(r)\right]^T$.

Thus, developing the formula for overcoming an obstacle using the dot product is as follows: The left (or right) obstacle movement depends on the value of $t_{d_{min,m}}$ if $\xi_m^T(r) > 0$ will override left or $\xi_m^T(r) < 0$ will override right. The construction of these constraints will provide effective and accurate obstacle avoidance operations, even if the vehicle must be stopped by obstacles ahead.

To avoid the convergence cases to related gradients near the center of the obstacle, it is necessary to change some values of ξ_{num},, if override left, $\gamma_m = -1$ and $\gamma_m = 1$ for override right. From this it is possible to construct the convergence function as follows:

$$g_{pass,m}(x; \gamma_m) \coloneqq \gamma_m \xi_m^T\left(t_{d_{min,m}}\right) n\left(t_{d_{min,m}}\right) + \xi_{num} \leq 0 \tag{18}$$

II.2 Cost function

In order to achieve optimal trajectory, it is necessary to treat the cost function with a minimum value and at the same time the constraints need to be separated. For handling emergency situations of autonomous vehicles, the idea is to reduce the vehicle's speed of movement to a minimum. In addition, the warning situation for performing emergency operations should be triggered before the vehicle is too close to the obstacle; if the vehicle is too close, the ability of computation is wrong about perception coefficient and the prediction will not certain, at the same time, if the small deviation in both position and direction from the reference curve will reduce the possibility of collision with the vehicle ahead, helping the autonomous system controls the motion trajectory.

In order to reduce the speed as fast as possible, the vehicle accelerator vector must be in the ellipse of the combined traction (Fig. 3) as $\left[\frac{a_t}{c_t}\right]^2 + \left[\frac{a_n}{c_n}\right]^2 \leq 1$ but if it is exact on the boundary, $\left[\frac{a_t}{c_t}\right]^2 + \left[\frac{a_n}{c_n}\right]^2 = 1$ at all times of motion and the effective matching of algebraic constraints to ensure the optimum is to assign the value $a_t = \dot{v} = u_2$ also substitutes the value u_2 in (5), from which the value $\dot{v}$ is defined as follows:

$$\dot{v} = -c_t\sqrt{1 - \left[\frac{v\dot{\theta}}{c_n}\right]^2} \tag{19}$$

Therefore, we do not need to calculate to reduce the velocity v in the cost function nor to see u_2 as the value of the separate variance function in the optimization process. Thus, the cost function J will be formulated by combining two components: the cost of motion and the cost associated with the obstacle as follows:

$$J(x, u_1) = J_{mov}(x, u_1) + J_{objs}(x) \tag{20}$$

Motion costs are calculated as follows:

$$J_{mov}(x, u_1) = \int_t^{t+T_{hor}} \left\{u_1^2 + \sum_{i \in \{v,a,j,\theta,k\}} k_i \Delta_i^2(x, u_1)\right\} dr \tag{21}$$

with $\Delta_v(x) = v[\theta - \theta_r]$ (22)

$$\Delta_a(x) = v^2[k - k_r] \tag{23}$$

$$\Delta_j(x, u_1) = v^2\left[\bar{k} - \bar{k}_r\right] \tag{24}$$

$$\Delta_\theta(x) = \theta - \theta_r \tag{25}$$

$$\Delta_k(x) = k - k_r \tag{26}$$

and $k \coloneqq \frac{\delta}{l\left|1 + \left[\frac{v}{v_{ch}}\right]^2\right|}$; $\bar{k} \coloneqq \frac{dk}{d\delta} u_1$; $\bar{k}_r \coloneqq \frac{dk_r}{ds}\dot{s}$

In which: $k_i > 0$, the proximate relative lateral velocity $\Delta_v \approx \dot{d}_r$, acceleration $\Delta_a \approx \ddot{d}_r$ and jerk $\Delta_j \approx \dddot{d}_r$

Since these equations perform multiplication by the velocity v it governs the trajectory cost at high speed and manages the velocity variation. However, when the speed returns to a low value just before the vehicle stops, these values decrease. Thus, equations (25) and (26) are constructed in which the value u_1^2 of the integral (21) is combined to make the vehicle perform a smooth stop operation.

The costs of the vicinity of the obstacles are not included in (20), because if they are taken into account, it will lead to undesirable effects. For example, the quicker the autonomous vehicle avoids obstacles, the smaller the time integration costs will be. Therefore, instead of considering the cost of the vicinity, the minimum distance $d_{min,m} = \min d_m$ to the perimeter of the vehicle (Fig. 4) shall be considered for each m object, which results in the total weight as follows:

$$J_{objs}(x) = \sum_{m=1}^{M} k_{objs,m}\, C_m(d_{min,m}(x)) \tag{27}$$

Here the cost function is calculated

$$C_m(.) = \left[\min(\left[(.) - d_{infl,m}\right], 0)\right]^2 \tag{28}$$

The affected regions $d_{infl,m}$ (Fig. 4) are chosen for the following reasons: first, it is independent from linear increasing cost and the value $d_{infl,m}$ has the cost of stacking between the obstacles; second, the volume of calculation is less; third, the cost is finite even $d_{infl,m}$ can still be less than 0 and this has reduced a few collisions that can occur with vehicles resulting from poor convergence. Finally, weaknesses or deficiencies of the system, as well as inaccurate prediction fault of an obstacle that may at least be at a certain level calculated by the weight $k_{objs,m} > 0$ and the remaining parameter is $d_{infl,m}$

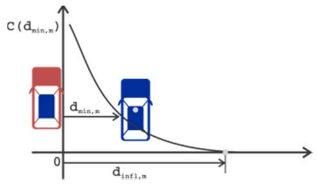

Figure 4. Distribution of costs in the vicinity of obstacles

II.3 Solution for contingency motion planning

The main idea to build a contingency motion planning consists of three stages:

Stage 1: Calculating the possibility of operating of surrounding objects to build the initial trajectory. Surrounding objects are objects ahead in the same lane or adjacent lane of the vehicle (in this study, we exclude the case of vehicles operating in the opposite direction and obstacles behind the vehicle). The initial motion trajectory of the vehicle is generated over a certain period of time T_{h1} and no collision occurs under the assumed operations of other vehicles.

Stage 2: In order to ensure safety when moving in the initial motion trajectory, all possible trajectories of the vehicles ahead must be considered [6]. The consideration and calculation of the trajectories of the vehicles ahead are performed by computing the ability to use the lane [6] with a certain period of time T_{h2} of the vehicles to be considered (Fig. 5), we will see the calculation and building the optimal trajectory p1 for a given time period $[t, t + t']$ and then trajectory *p2* is set to operate without collision. Finally, the motion trajectory of the vehicle is a combination of two trajectories *p1* and *p2* according to time T_{h2}, and this trajectory does not intersect with the space set by the trajectories of the vehicles ahead at any time during the period of time T_{h2}. Therefore, for a certain period of time with any trajectories of vehicles ahead, the operating system of the autonomous vehicle can perform an emergency operation to stop the vehicle safely and the solving system turns to stage 3.

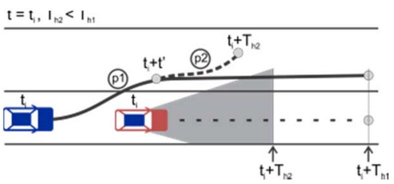

Figure 5. The vehicle's motion planning based on the operating trajectories of the vehicle ahead

Stage 3: Implementing the evaluation the standards to assure its safety (distance to the vehicle ahead, the space generated by set of trajectories of the vehicle ahead), then the solving system will provide assessment if contingency trajectory should be performed or not for safety or continue to operate in the initial optimal trajectory (Fig. 6). In the case at point $[t_{i+1}, t']$, if there exists an operation to connect the p3 initial optimal trajectory with the p4 emergency trajectory without intersecting with the vehicle ahead's occupied space, the p3 optimal trajectory p3 is chosen; otherwise, if there is no other collision-free trajectory, the p2 contingency trajectory is calculated earlier will be connected to the initial trajectory.

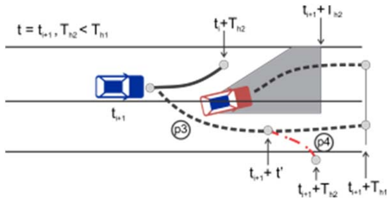

Figure 6. Evaluating safety conditions to perform the motion process

II.3.1 Building optimal trajectory

In order to generate optimal trajectory when establishing motion for autonomous vehicle, it is necessary to take into account operating capability of the vehicles ahead according to their motion trajectories. Many studies have been conducted on possible trajectories computing techniques of vehicles ahead, as in study [1] to calculate the trajectory of the vehicle ahead, by assuming constant yaw rate and acceleration (CYRA) is used or in study [2] by using a maneuver recognition module (MRM) to determine the motion trajectories of the vehicles ahead. Both methods have their own advantages, for MRM, the predictive results are more accurate than CYRA and vice versa CYRA give results with a longer time prediction [2]. In this study, we perform generating (an) optimal trajectory based on the idea of MRM, generating possible trajectories prediction of the vehicle ahead based on target lane detection, i.e. the lane in which the vehicles ahead are moving, and at the same time basic moves such as lane-keeping, lane-change or left/right turns manoeuvres are also considered for predictive situations.

To calculate the most likely trajectory, comparing the current path and the center position of the lane should be performed to provide the most likely trajectory prediction for at each time point t_i in period of time T_{h1}. In addition, at each time t_i a polygon region generated by the trajectories representing each vehicle ahead will be calculated and these predictions are used as constraints in generating motion trajectories for autonomous vehicles.

In the interval T_{h1}, after the possible trajectories of the vehicles ahead are determined, the selection for generating the optimal trajectory will be performed and this trajectory generated with the main aim is to avoid collisions through reducing vehicle's speed and avoiding vehicle shake, jerk in order to create a smooth trajectory. Therefore, the cost function (20) is changed to control the deviation from the reference trajectory (the central location of each lane) and to avoid the predictions of the vehicle(s) ahead.

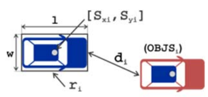

Figure 7. Constrains to avoid obstacles

Thus, each vehicle ahead $OBJS_i$ $i \in \{1 \dots n\}$ will have a space region prediction representing at each time i and constraints related to the distance between the generated trajectory and the predicted objects have to be considered to avoid collisions with vehicles ahead. The minimum distance d_i between the rectangle r_i surrounding the vehicle and the predictive area of the vehicle(s) ahead $OBJS_i$ is calculated at time i (Fig. 7) as follows:

$$d_i = \min_i distance\,(r_i, OBJS_i) \quad (29)$$

and the minimum distance d_i will be compared with a parameter λ to determine if there is a collision with the vehicle $OBJS_i$ or not, the minimum value of the cost function will minimize the variation of the speed and steering mode as follows:

$$J_1 = \int_t^{t+T_{h1}} [\gamma_1 u_1^2 + \gamma_2 u_2^2 + \gamma_3(\theta - \theta_r)^2 + \gamma_4 \delta^2 + \gamma_5 d_r^2]\, dr \quad (30)$$

Where: satisfies the conditions (1) - (5), (10) - (15) and θ_r is the direction of the reference trajectory; dr is the distance to the reference trajectory; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ are weighted parameters.

Here the reference trajectory is defined as the center of the current lane, in the case if no viable trajectory is found when using the center of the current lane as a reference, then the center of the adjacent lane as the reference trajectory (Fig. 8). A new trajectory is generated corresponding to a lane change adjustment and consideration of the constraints associated with the distance between the generated trajectory and the predicted trajectories of the other participating vehicles calculated by the formula (29) will help the autonomous vehicle avoid collisions with the surrounding vehicles.

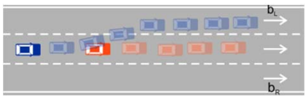

Figure 8. Generating optimal trajectory

II.3.2 Building an emergency trajectory

In the process of participate in traffic, the vehicles ahead can perform many unpredictable and incomputable operations when building the optimal trajectory for autonomous vehicles. However, not all the vehicle ahead's operations can result in a collision, so for a period of time T_{h2} the autonomous vehicle must maintain an emergency operation aming at solving all possible actions of the vehicle(s) ahead.

Based on the idea of the method implemented in [6], it is to define a region that surrounds all possible trajectories of the vehicle ahead for a given time period T_{h2} to build an abstract model with satisfied physical constraints. The constraints are assumed to predict the ability of the area occupied by the vehicle ahead to drive back and out from the forbidden road, the maximum absolute acceleration will be limited by the value a_{max}, vertical acceleration is zero when velocity reaches a value of v_{max} and this value is inversely proportional to velocity when velocity is greater than a certain v_s parameter.

If one of the constraints is not satisfied, the corresponding abstract model of the vehicle will not be considered when building the occupied area of the vehicle ahead. The approach to this abstract model has the advantages of ensuring that all possible trajectories of the vehicle ahead are in the vicinity generated by the set of trajectories. Therefore, the computation to build optimal trajectory and to avoid collisions that will fit and reach real-time computational efficiency.

Similar to the optimal trajectory building, the non-collision emergency contingency trajectory building is performed after being calculated to predict the trajectory of the vehicle ahead. The difference in emergency contingency building is that the emergency operation is accomplished by reducing the vehicle speed to the possible point and avoiding all possible trajectories of the vehicle ahead by occupied area as presented.

Thus, the cost function is built to produce the optimal trajectory described in (30) with the difference that velocity v decreases to a minimum over time T_{h1}:

$$J_2 = \int_t^{t+T_{h1}} [\gamma_1 u_1^2 + \gamma_2 u_2^2 + \gamma_3(\theta - \theta_r)^2 + \gamma_4 \delta^2 + \gamma_5 v^2]\, dr \quad (31)$$

Where: satisfies the conditions (1) - (5), (10) - (14), $(S_y, S_y) \in lanes \backslash OBJS_i$ and θ_r are the direction of the reference trajectory; dr is the distance to the reference trajectory; $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5$ are weighted parameters.

III. EXPERIMENTAL RESULTS

To test and evaluate the solution presented, we conduct empirical simulations of processes in the Matlap environment. In which the calculations (using the SI system) with the sampling interval of 0.1s and the optimal limit $T_{hor} = 3.0s$, the chosen weights are $[k_v; k_a; k_j; k_\theta; k_k] = [10^3; 10^2; 10^1; 10^2; 10^1]$, the value of the affected area $d_{infl,m} = 1.0m$ is calculated by the system number $k_{obst} = 10^5$. During the simulation, vehicles with trajectory recorded will be considered as vehicles ahead and the autonomous vehicle will be located behind these vehicles.

Parameters used to generate contingency trajectories are $T_s = 0.8s$; $T_{h1} = 6s$; $T_{h2} = 2s$; $\varepsilon = 2.5m$; $v = [0,50]m/s$; $a = [-10,10]m/s^2$; $\theta = [-\frac{\pi}{2}, \frac{\pi}{2}]rad$; $\delta = [-0.5, 0.5]rad$; $w = 1.5m$; $l = 5.0m$; $v_{ch} = 50m/s$ and the model is predicted with $v_{ch} = 60m/s$; $d_{max} = -d_{min} = 0.5rad/s$; $d_{max} = 2.0m$; $d_{min} = -2.0m$; $c_n = c_t = 10.0m/s^2$. The trajectories move to the I/O controller with a simulation time cycle of 0.01s.

In order to ensure objectivity and reliability of the evaluation, we conducted simulations with three different scenarios in which the first simulation scenario found motion planning without considering operations to generate contingency trajectories The others apply this operation with different parameters for a comparative assessment.

Scenario 1. When motion planning for autonomous vehicle, only the predicted trajectories of the vehicles ahead are calculated and the traffic scenarios are constructed as follows: To start, the autonomous vehicle and other vehicles are located in a lane with the distance from the autonomous vehicle to the vehicles ahead is 40m, the initial velocity of the vehicle ahead is 15m/s and the autonomous is 20m/s. At the point of 5s (T10) the vehicle ahead drives to the left lane, because there is no operation generating emergency contingency trajectory situations, this scenario will occur accident. (Fig. 9).

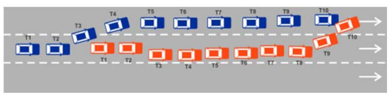

Figure 9. Simulation results of scenario 1

Scenario 2. Also with the same scenario as scenario 1, in this scenario, the motion plan of the autonomous vehicle is supplemented with actions to create contingency trajectory and predict motion ability of the vehicles ahead at every step of the time. Therefore, all the motions of the vehicles ahead are considered and a contingency trajectory will be triggered in the event of an emergency, also at the point 5s (T10) a vehicle ahead moving off the lane and driving to the left in front of the autonomous vehicle. This unusual lane-change behavior has resulted in the vehicle having to trigger a state of emergency and launch a backup trajectory to avoid collisions (Fig. 10).

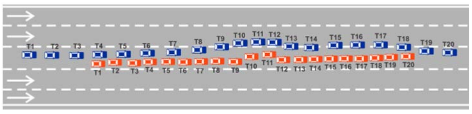

Figure 10. Simulation results of scenario 2

Scenario 3. In this scenario, two vehicles joining the traffic in front of the autonomous vehicle will be considered, the initial distances between the autonomous vehicle and the vehicles ahead are 40m and 70m, respectively, the initial velocity of the vehicles are 15m/s and 20m/s. Figure 11 shows the movement status of the vehicles ahead at each time step along with the trajectory generated by the autonomous vehicle. The simulation scenario is as follows: at time T the vehicle ahead OTO1 performs lane-change to the left where the autonomous vehicles are moving, similar to scenario 2, the autonomous vehicle launch emergency situation and activate the motion contingency trajectory in motion planning to avoid collision with the OTO1. Next, at time T20, the vehicle ahead OTO2 begins to change lane, but the lane-change situation of OTO2 is not a dangerous situation, so the autonomous vehicle does not start the emergency situation and use the contingency trajectory. At this time and the following periods, the autonomous vehicle continues to move in its trajectory. Thus, the simulation will not occur collision.

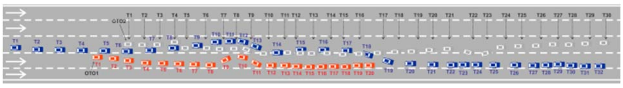

Figure 11. Simulation results of scenario 3

Since autonomous vehicles can move a significant distance in a short period of time (a fraction of a second), the time taken to perform calculations and suggested optimal solution cannot be ignored. Therefore, in the implementation process, the expected delay time according to prediction as in [8] and the stability of the predictive model should be applied, this nonlinear optimization problem can be realized sequentially [8] by the conventional Runge-Kutta method (RK2) with a step size of 0.02s.

IV. CONCLUSION

This paper proposes a contingency motion planning solution to ensure the safety for autonomous vehicle, the optimal feature of this solution is to achieve by considering the possible trajectories of the vehicles ahead. The safety factor of this solution is performed by keeping a system to calculate any possible trajectories of the vehicles ahead in a certain period of time. At the same time, the model used for predictive control will be bound by factors such as acceleration, vehicle braking force and the combined force of the wheel, as well as additional constraints such as lane width and desired travel direction.

The key idea of this technical solution will support the design of autonomous vehicles with a safe stop, no matter what the controlling of the current vehicle is. The empirical simulation with the given scenarios reveals that the safety factor can be achieved by calculating to examine all possible possibilities of the vehicles ahead. In the future, in order to increase the reliability of this solution, the settings being experimentally simulated will be transferred to the real environment with experimental vehicle fully equipped with sensors, at the same time add some factors to analyze the stability of the coupling system so that traffic behavior is more accurately predicted.

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