Path planning algorithm of the intelligent vehicle considering the passenger feelings

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Abstract. As the autonomous driving vehicle becomes popular, the driver will be completely replaced by autonomous system, but passengers in the vehicle will always exist. Autonomous vehicle has the essential property of transporting people, so the passenger comfortability should be fully considered. In this paper, based on the trust between the passenger and the driver, the passenger physical and psychological feelings are comprehensively considered. Through the real track test data, the support vector machine is used to establish the passenger feeling evaluation model -- to show the relationship between the passenger and the autonomous driving system. And then, based on the evaluation model, a new path planner algorithm is proposed, which is proved by simulation that the re-planning path can significantly improve the passenger comfortability.

1. Introduction

With the further development of intelligent driving technology, the rampant technological improvements suggested that, autonomous vehicles future deployment would not be restricted by computational or sensory limitations [1]. Obviously, the passenger comfortability is very worthy of attention, and it will become a key link to restrict the intelligence degree of vehicles. Self-driving passenger vehicles, with the essential property of transporting people, should fully consider the comfortability of human.

In the field of classic vehicle research, the passenger feelings are mainly considered by the response of the human body to vibration [2]. However, the vibration mostly comes from the acceleration effects in the vertical direction, and most of these effects depend on the smoothness of the road and the suspension performance, that is, the acceleration effects are less related to the control method of the driving system. Therefore, the vibration in the vertical direction is not the focus of this study, and only the influence in the lateral and longitudinal motions is considered in this paper.

Furthermore, the current study of the passenger comfortability is almost based on the physical feelings of human, and there is no specific evaluation standard for the psychological feelings. A trust model, proposed by Muir [3] in 1994, presents the degree of trust between human and autonomous system, which provides a research framework for whether human chooses to interfere with the instruction of autonomous system or not. However, for high-level self-driving vehicles, the passengers do not have the ability like a supervisor, and it is totally up to the system to plan the motion of the vehicle in a way, that does not put too much stress on the passengers and does not decrease their level...
of comfort [4]. To establish the trust model, the approach Muir adopted was to take models of trust between people as a starting point and extend these to apply to the human/machine relationship [5]. Similarly, in order to study the trust feeling of the passenger and the autonomous driving system, it is advantageous to take trust feeling between the passenger and the driver as a starting point.

Recent researches on the feelings of the people in the autonomous driving vehicle is mostly concentrated on the driver seat. For example, based on the actual obstacle avoidance test path data of three drivers, Noriyasu Noto etc. [6] correct the potential field parameters of the artificial potential field. And the new path obtained from the corrected artificial potential field has the personality of the driver. However, not all drivers' operations make passengers feel reliable and comfortable. To truly solve the passenger comfortability problem, it is more important to study the passenger feelings.

The paper [2] believes that lateral acceleration and the its rate can be used as indicators to evaluate comfortability of the passengers. Mohseni [7] also defines the discomfort as high jerk and acceleration in the cost function of the autonomous driving control algorithm. However, the indicators related to the comfortability are not limited to acceleration and its rate. [2,7] do not discuss the possible correlation of the remaining indicators, and ignore the coupling relationship may exist, such as the "tolerance" degree of the passengers of the lateral acceleration when the vehicle drives at different speeds.

The purpose of this paper is to establish a passenger feeling evaluation model (PFEM) and design a new path planning algorithm combined with the evaluation model. The inputs of PFEM are the vehicle dynamic indicators in the lateral and longitudinal directions. The output is the subjective evaluation indicator that comprehensively considers the passenger's physical and psychological feelings.

The research idea of this paper is shown in the Figure 1 below.

![Figure 1. Research idea of the paper.](image)

2. Track tests and data collection

This section describes the target task and experimental setup of track tests.

2.1. Target task

As mentioned above, PFEM mainly focuses on the influence in the lateral and longitudinal motions of vehicle. Therefore, the designed real track tests should be able to simultaneously collect the dynamic indicators of the vehicle in the lateral and longitudinal directions and corresponding subjective feeling evaluation of the passenger. In order to ensure the reliability of the model, the test conditions should cover the full range of the passenger feelings.

2.2. Test scenarios

The turning scenario and obstacle avoidance scenario are selected, and these two scenarios have covered most common lateral motion control scenarios of autonomous driving.

In order to reflect changes of the passenger feelings between different driving operations, ten drivers (five male and five female) are tested for all tests. On the other hand, in order to ensure the accuracy of subjective feelings, each test was equipped with two passengers in the vehicle. And the
average value of the final scores of the two passengers is taken as the final subjective score. In addition, if the deviation of scores between two passengers is too large, the test data will not be used.

2.2.1. Turning scenario.
This test process is divided into four sections, as shown in Figure 2.
1. Acceleration section: The driver starts to drive the test vehicle and accelerate to the maximum speed which the driver believes he/she can safely pass the ahead curve with (radius is set as 25m, 30m, 35m for three tests).
2. Steady state section: The driver should hold the speed and keep the vehicle moves along the lane.
3. Test section: The driver keeps the speed to pass the curve. When the driver starts to operate the steering wheel to enter the curve, it is the moment the passenger starts to pay attention to his physical and psychological feelings. After that, the driver controls the vehicle move in the curve with a constant speed as much as possible, and the passenger needs to notice his feelings until the vehicle has completely passed the curve.
4. End section: The driver drives completely out of the turning lane, then decelerates and stops safely. A questionnaire is finished by the passenger.

![Figure 2. Turning scenario.](image)

2.2.2. Obstacle avoidance scenario
The test process is also divided into four sections, as shown in Figure 3.
1. Acceleration section: The driver starts to drive the test vehicle and accelerate to the expected speed (speed is set as 30km/h, 60km/h, 80km/h for three tests).
2. Steady state section: The driver keeps the vehicle move along the lane with the expected speed.
3. Test section: The driver keeps the expected speed and controls the vehicle move towards the obstacle. When deciding to operate the steering wheel to avoid the obstacle, the driver should approach the obstacle as close as possible according to his/her own judgement. After that, the driver controls the steering wheel to make the vehicle avoid the obstacle and enter the left lane with a constant speed. When the driver starts to operate the steering wheel to make the vehicle enter another lane, it is the moment the passenger pays attention to his physical and psychological feelings until the vehicle safely moves along the left lane.
4. End section: The driver keeps the vehicle move along the other lane, then decelerates and stops safely. A questionnaire is finished by the passenger.
2.3. Data collection

This section describes the objective and subjective data collection and processing method.

2.3.1. Objective indicators

The test vehicle was equipped with gyroscope to record the vehicle dynamic indicators in the test process. This paper only considers the dynamic parameters in the lateral and longitudinal direction, so the collected indicators mainly include: longitudinal speed, lateral acceleration and yaw rate. For the integrity of the indicators, the collected indicators are derived, and the final indicators are determined as shown in the following Table 1.

| Indicators       | Derived indicators       |
|------------------|--------------------------|
| Longitudinal speed | None                     |
| Lateral acceleration | Rate of lateral acceleration |
| Yaw rate          | Yaw angular acceleration |

For both test scenarios, this paper focuses on the data collected in the test section shown in the Figure 2 and Figure 3. For example, Figure 4 shows the data collected in a certain obstacle avoidance test. In this scenario, this paper only uses the data in the lane change process, as the time period T. And the statistical values of the indicators in the T section are taken as the alternative objective indicators.
2.3.2. Subjective indicators
The passenger feelings are subjective indicators, so we adopted the form of questionnaire to collect the evaluations. The scope of questionnaire includes passengers' physical and psychological feelings, and the questions mainly cover the following four dimensions.
1. The degree of shaking feeling during the lane change (turning).
2. The sudden degree of steering operation.
3. The degree of nervousness during the lane change (turning).
4. The degree of consistency between the driving behavior and passengers’ safety expectations.
In the actual questionnaire, the subjective evaluation of each dimension is obtained through a scale of 1-5, and the final score is the weighted summation of four dimensions. Table 2 shows the subjective evaluation results corresponding to the test of obstacle avoidance of Figure 4. The weight of each dimension is obtained by analytic hierarchy process [8].

Table 2. Subjective evaluation result of the obstacle avoidance scenario in Figure 4.

| Evaluation dimensions | Passenger 1 | Passenger 2 | Weights |
|-----------------------|-------------|-------------|---------|
| 1                     | 2           | 3           | 0.09    |
| 2                     | 4           | 3           | 0.13    |
| 3                     | 5           | 4           | 0.30    |
| 4                     | 4           | 4           | 0.48    |
| Final score           | 4.12        | 3.78        |         |

Based on the actual vehicle test, 86 sets available samples were obtained. In order to facilitate the modeling of PFEM, this paper divides the subjective evaluation indicators into three dimensions evenly based on the scores, as shown in Table 3, $E_{pf}$ is the subjective evaluation level of passengers.

Table 3. Subjective evaluation classification.

| $E_{pf}$ | Score range | Category | Sample size |
|---------|-------------|----------|-------------|
| 1       | [4, 5]      | Good     | 32          |
| 2       | [2.7, 4)    | Normal   | 34          |
| 3       | [1, 2.7)    | Bad      | 20          |

3. PFEM based on Support Vector Machine
In this paper, the relationship between objective parameters of vehicle dynamics and subjective evaluation is established by Support Vector Machine (SVM).
SVM has many unique advantages in dealing with the small sample, nonlinear and high dimensional pattern recognition problems [9]. In addition, SVM is a convex optimization problem, the local optimal solution must be global optimal solution, preventing overlearns problems.
The classification principle of SVM is to find a hyperplane, which divides the different types of samples in the training sample, so it is mainly used in the two classification cases. However, as mentioned above, the subjective feeling scores are divided into three categories. This paper adopts the "one-to-one" method to realize multi-classification of SVM. Three SVM classifiers are trained to achieve distinction of "Bad and Normal", "Good and Bad" and "Good and Normal", and the final category of the sample is determined by the voting result of each SVM.
For the training of PFEM, 1/3 of available samples are taken as test samples, and the rest are used as training samples. A multi-classification model is generally evaluated by accuracy and macro-average F1 value. The accuracy rate includes the training sample accuracy rate and the test sample accuracy rate. The macro-average F1 value (Micro-F) is the arithmetic mean of the F1 value for all classes, which can make significant evaluation of the effectiveness of classification. In order to make full use of all samples, the Leave-One-Out-Cross-Validation (LOOCV) is also used to calculate the accuracy of SVM.
This paper builds the SVM model in MATLAB, and compares the SVM with different kernel functions. The training results are shown in Table 4.

| Kernel function     | Training sample accuracy | Test sample accuracy | Micro-F | Accuracy of LOOCV |
|---------------------|--------------------------|----------------------|---------|-------------------|
| Linear kernel       | 77.27%                   | 73.82%               | 0.733   | 70.93%            |
| Polynomial kernel   | 63.64%                   | 43.18%               | 0.712   | 56.97%            |
| RBF kernel          | 89.82%                   | 86.36%               | 0.859   | 83.72%            |
| Sigmoid kernel      | 72.73%                   | 56.82%               | 0.566   | 68.60%            |

Obviously, SVM with RBF kernel can get better classification results. According to the above analysis, the SVM with RBF kernel can establish PFEM with high accuracy. And PFEM can be expressed as the following equation:

\[ E_{pf} = f_{SVM}(V_{indictor}) \]  

where, \( E_{pf} \) is the subjective evaluation level of the passenger; \( V_{indictor} \) is a vector of the statistical values of each indicator in Table 1.

4. Path planner based on Model Predictive Control

Model Predictive Control (MPC) is an important control method in the theory of predictive control. An important step of MPC for path planning is to predict the future behavior of the vehicle at each time step based on the prediction model. This future prediction determines the control inputs within a specified prediction horizon, and on the basis of these future states, a performance index is minimized to compute the optimal control inputs.

4.1. Predictive model

This section describes the vehicle model used for simulations and control design. This paper uses a “bicycle model” to describe the dynamics of the vehicle as follow, which is obtained according to Newton’s laws.

\[
\begin{align*}
mx'' &= m\dot{y}\ddot{\phi} + 2(F_{xf} + F_{xr}) \\
my'' &= -m\dot{x}\ddot{\phi} + 2(F_{yf} + F_{yr}) \\
I\ddot{\phi} &= 2(aF_{yf} - bF_{yr})
\end{align*}
\]  

where \( I \) is the vehicle moment of inertia about the yaw axis; \( a \) and \( b \) are the longitudinal distances from the CG of vehicle to the front and rear wheels, respectively.

Such model captures the most relevant nonlinearities associated to lateral stabilization of the vehicle. Figure 5 depicts a diagram of the vehicle model, which has the following longitudinal, lateral and turning or yaw degrees of freedom.

Under the condition of small side angle and small lateral acceleration, the tire model is approximately linear, so the longitudinal and lateral tire forces for each tire are given by

\[
\begin{align*}
F_{l*} &= C_{l*} s_* \\
F_{c*} &= -C_{c*} \alpha_*
\end{align*}
\]  

where, \( * \in \{ f, r \} \) denote the front and rear axles, \( s_* \) is the slip ratios, and the tire slip angles \( \alpha_* \) represent the angle between the wheel velocity and the direction of the wheel itself, so it is defined as

\[
\alpha_* = \tan^{-1} \frac{v_{c*}}{v_{l*}}
\]  

where, \( v_{l*} \) and \( v_{c*} \) are the longitudinal and lateral wheel velocities respectively.
Then, the vehicle model can be written in the nonlinear state-space form as:

\[
\begin{align*}
    m\ddot{y} &= -m\dot{x}\dot{\phi} + 2C_{cf}\left(\delta_f - \frac{\dot{y} + a\dot{\phi}}{\dot{x}}\right) + C_{cr}\frac{b\dot{\phi} - \ddot{y}}{\dot{x}} \\
    m\ddot{x} &= m\dot{y}\dot{\phi} + 2\left[C_{lf}\dot{y} + C_{cf}\left(\delta_f - \frac{\dot{y} + a\dot{\phi}}{\dot{x}}\right) + C_{lr}\dot{\phi}\right] \\
    I_\phi\dot{\phi} &= 2\left[aC_{cf}\left(\delta_f - \frac{\dot{y} + a\dot{\phi}}{\dot{x}}\right) - bC_{cr}\frac{b\dot{\phi} - \ddot{y}}{\dot{x}}\right] \\
    \dot{Y} &= \dot{x}\sin\phi + \dot{y}\cos\phi \\
    \dot{X} &= \dot{x}\cos\phi - \dot{y}\sin\phi
\end{align*}
\](6)

The nonlinear state-space can be described by the following compact differential equation:

\[
\dot{\xi} = f(\xi, u)
\](7)

where the state and input vector are \(\xi = [\dot{y}, \dot{x}, \phi, \dot{\phi}, Y, X]\) and \(u = [\delta_f]\).

Write the system into the following discrete-time nonlinear system:

\[
\xi(k + 1) = f(\xi(k), u(k))
\](8)

Consider the state \([\xi_0, u_0]\), \(\xi_0(k)\) is obtained by applying the input sequence \(u_0(k)\) for \(k \geq 0\), to the system (8)

\[
\xi_0(k + 1) = f(\xi_0(k), u_0(k))
\](9)

Then the system (8) can be approximated into the following system by Taylor expansion:

\[
\xi(k + 1) = A_{k,0}\xi(k) + B_{k,0}u(k) + e_{k,0}
\](10)

where

\[
A_{k,0} = \left.\frac{\partial f}{\partial \xi}\right|_{\xi_0, u_0}, B_{k,0} = \left.\frac{\partial f}{\partial u}\right|_{\xi_0, u_0}
\](11)

\[
e_{k,0} = \xi_0(k + 1) - A_{k,0}\xi_0(k) - B_{k,0}u_0(k)
\](12)

Taken together, at each time we can consider the system as

\[
\xi(t + 1) = A_{t,0}\xi(t) + B_{t,0}u(t) + e_{t,0}
\](13)
Based on this linear time varying model, it is convenient to predict the vehicle state in the prediction horizon through MPC.

4.2. Objective function

4.2.1. Tracking function

During path re-planning, the deviation between the predicted path and the reference path needs to be calculated, as shown in the Figure 6.

![Figure 6. The deviation between the predicted path and the reference path.](image)

Assume that the global X direction is along the road, the deviation between the predicted path and the reference path is \( |Y_{pre} - Y_{ref}| \), which is under the same \( X_{pre} \). Therefore, the tracking function could be written in this way,

\[
J_{track} = S_{track} (Y_{pre} - Y_{ref})^2 |_{X_{pre}}
\]

where, \( S_{track} \) is the weight, \( Y_{pre} \) is the \( Y \) coordinate value of the predicted path, \( Y_{ref} \) is the \( Y \) coordinate value of the reference path.

4.2.2. Obstacle avoidance function

For autonomous vehicles, obstacle information is usually given by sensors such as lidar. The design idea of obstacle avoidance function is to adjust the value according to the distance deviation between the obstacle point and the target point. The closer the distance is, the larger the value of the function is. Considering the influence of vehicle speed, the following obstacle avoidance function is selected.

\[
J_{obs} = S_{obs} \left( \frac{v_x^2 + v_y^2}{(x_i - x_c)^2 + (y_i - y_c)^2 + \epsilon} \right)
\]

where, \( S_{obs} \) is the weight; \( v_x, v_y \) are the longitudinal and lateral velocity of the vehicle respectively; \( (x_i, y_i) \) represents the coordinates of the obstacle point, \( (x_c, y_c) \) represents the coordinates of the center of mass of the vehicle, \( \epsilon \) is a tiny positive value.

4.3. MPC path planner combined with PFEM

The path planner provides re-planning path information to path tracker according to a certain sampling period. Each re-planning process calculates the re-planning path based on the prediction model, and in the meantime, the vehicle dynamics state \( \xi = [\dot{y}, \dot{x}, \phi, \dot{\phi}, Y, X] \) in the predicted time domain can also be calculated. Based on these state variables, the input of the PFEM can be calculated, then the subjective feelings of each re-planning path are obtained.

The simulation scenario designed is same as the one in the Figure 3. A stationary obstacle is set in the middle of the route, and the global reference path is a straight line along the center of the road.

According to section 4.2, the cost function of MPC path planner can be written as
\[ J_1 = \min \sum \left( \frac{S_{\text{obs}}(v_x^2 + v_y^2)}{(x_i - x_c)^2 + (y_i - y_c)^2 + \varepsilon} + S_{\text{track}}(Y_{\text{pre}} - Y_{\text{ref}})^2 \right) \]

Set speed as 60km/h, \( S_{\text{obs}} = 30 \), \( S_{\text{track}} = 10 \), the result of simulation is shown in Figure 7.

![Figure 7](image_url)

**Figure 7.** The result of simulation with cost function \( J_1 \).

Put PFEM into the cost function

\[ J_2 = \min \sum \left( J_{\text{obs}} + J_{\text{track}} + S_{\text{PFEM}}E_{pf} \right) \]

Set same speed, \( S_{\text{obs}} = 30 \), \( S_{\text{track}} = 10 \), \( S_{\text{PFEM}} = 10 \), the result of simulation is shown in Figure 8.

![Figure 8](image_url)

**Figure 8.** The result of simulation with cost function \( J_2 \).

Compare with the Figure 7, the \( E_{pf} \) of re-planning path in Figure 8 get improved.

In order to recognize the impact of the new path planning algorithm on the passenger feelings in actual driving path. By collecting the dynamics of the simulated vehicle, the \( E_{pf} \) at each position on the actual driving path is calculated. As shown in the Figure 9.
Figure 9. The result of simulation with cost function $J_1$ and $J_2$.

The comparison shows that the new cost function can significantly improve the passenger feelings on the driving path.

5. Conclusion

The study of this paper mainly focuses on the passenger feelings of the self-driving vehicle. In order to solve the problem of passenger feelings from the planning level of autonomous system, this paper designed a real track test to collected data, and build an evaluation model to reflect the passenger subjective feelings from objective dynamic indicators of vehicle. The SVM with RBF kernel is used to build the PFEM with 83.72% accuracy. Then, based on the MPC path planner, this paper proposes a new cost function to calculate the re-planning path, and the simulation result showed that the new planner can significantly improve the passenger comfortability.

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