공학석사학위논문

적응식 가중 행렬 최적 제어에 기반한 사륜 독립 조향 구동 차량의 경로 추종 제어

Path Tracking Control of Four Wheel Independent Steering and Driving Autonomous Vehicle Based on Adaptive Weight Optimal Control

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Abstract

Path Tracking Control of Four Wheel Independent Steering and Driving Autonomous Vehicle Based on Adaptive Weight Optimal Control

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An optimal controller applying an adaptive weight strategy is designed for path tracking control of a four-wheel independent steering and driving (4WISD) vehicle. This system changes the driving mode and modifies the priority of states according to the driving situation to improve the overall performance of the vehicle. It is implemented by modifying the performance index of an optimal control according to the predicted states using model predictive control (MPC). To do this, a dynamic model and a path tracking model of a 4WISD vehicle are determined and used as reference models for MPC. The path tracking controller is designed using MPC, and tracking performance is secured through state constraint conditions. The proposed adaptive weight strategy modifies the coefficients of the performance index depending on the expected driving conditions. In this study, the future state values of the MPC are used as the expected driving conditions. Lastly, the adaptive weight function is optimized through learning using an evolutionary strategy. The fitness function of the evolutionary strategy includes the conditions of a vehicle that are not considered by the path tracking model such as ride comfort. Handling stability and ride comfort are optimized while maintaining the lateral position error within criteria, using the constraints of MPC and optimization of adaptive weight function. Learning and simulation were conducted in a MATLAB/CarSim environment. The proposed method is compared with conventional models, and the verification results for lateral position error, yaw rate error, lateral acceleration and lateral jerk are presented to confirm the improvement of the overall performance of the vehicle.

Keyword: path tracking control, model predictive control, adaptive weight matrix, evolution strategy, four-wheel independent steering and driving

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Nomenclature

a_y	lateral acceleration of vehicle
γ	yaw rate of vehicle
v_x	Longitudinal velocity of vehicle
v_y	Lateral velocity of vehicle
M	Mass of vehicle
I_z	Yaw moment of inertia of vehicle
F_{xi}	Tire longitudinal force of i wheel
F_{yi}	Tire lateral force of i wheel
F_{zi}	Tire vertical force of i wheel
δ_i	Steering angle of i wheel
l_i	Distance from center of mass to i wheel
L	Wheelbase
B	Track
M_z	Yaw moment
M_{za}	Additional yaw moment
α_i	Tire slip angle of i wheel
C_i	Cornering stiffness of i wheel
ψ	Heading angle of vehicle
ψ_d	Heading angle of desired path
y	Lateral position of vehicle
y_d	Lateral position of desired path
κ	Curvature of desired path

Chapter 1. Introduction

1.1. Study background

In recent years, the paradigm of automobiles has changed rapidly to autonomous driving and electrification. Autonomous driving can prevent accidents caused by human drivers by tracking the desired path with guaranteed performance. Meanwhile, an electric vehicle using an electric motor as a driving source not only positively affects the environment by reducing harmful emissions but also has a fast control response. These characteristics facilitate more accurate control and improved stability and performance of an autonomous vehicle compared to conventional internal combustion engine vehicles. With these advantages, autonomous driving and electrification are already becoming a large trend in the automobile industry.

Furthermore, not only the driving system but also the chassis system is being electrified. Vehicle chassis systems such as brakes, steering, and suspensions are developed into by-wire modules with no mechanical connection. Each of these modules is integrated into one modular system called the e-corner module (ECM). Accordingly, a new electric vehicle platform is expected. The structure of future electric vehicles is expected to be integrated with ECM on a skateboard platform including batteries. This structure is not only suitable for autonomous vehicles but also increases the design freedom and cabin compatibility. In terms of control, this structure has the characteristics of four wheels operating independently.

The vehicles with four-wheel independent steering and driving (4WISD) have more control inputs than conventional vehicles. In addition, path tracking control affects not only tracking performance but also the overall performance of the vehicle, such as handling stability and ride comfort. In summary, the path tracking control problem of 4WISD vehicles is a form of multimodal function problem, which needs to deal with many control inputs. Therefore, optimal control is widely used for path tracking control of 4WISD vehicles.

In previous studies, the path tracking performance is compared with active front steering (AFS), direct yaw control(DYC), and 4WIS using linear quadratic regulator (LQR)[Mashadi11]. The method using LQR and feedforward control is applied to obtain steering angles under high speed trajectory tracking condition [Liu18]. The front and rear steering angles are obtained using sliding mode control for path tracking [Lei22]. In consideration of desired yaw rate and desired side slip angle, not only path tracking but also handling stability was studied. The rear wheel steering angle is obtained using nonlinear model predictive control (MPC) and the steering angles and additional yaw moment are obtained using robust control and optimal control to improve performance of path tracking and handling stability [Yu21, Hang17]. A parameter varying model with longitudinal velocity integrated into the path follow controller was controlled using LQR [Hang21].

In summary, the 4WISD vehicle is controlled by various methods for various object such as path tracking, handling stability, and longitudinal velocity control. However, the above studies only specified appropriate values of the weight matrix of performance index but did not express the derivation process and optimality. In addition, the previous studies have not considered factors that cannot be expressed in path tracking models, such as the ride comfort.

This paper focused on the fact that the weight matrix of the performance index determines the priority of the vehicle performance and the various driving modes of the 4WISD vehicle. By changing the ratio of the state weight matrix, it is possible to determine whether the position error or the handling stability is prioritized. Modifying the input weighting matrix can also determine whether to use front or rear wheel steering actively, or how much torque vectoring is performed.

1.2. Purpose of the research

A new method has been proposed to tailor the driving mode and performance index of an optimal controller to the driving conditions, which increases the overall performance of vehicle. The method is realized by modifying the weight matrix of the optimal control performance index according to the future states predicted by the MPC.

To do this, the followings process has been conducted. First, a dynamic model and a path tracking model were determined as the reference model of the MPC. Second, the path tracking controller was designed using MPC. By applying state constraints to MPC, it is possible to secure path tracking performance that satisfies the criteria such as lateral position and heading angle errors. Third, the adaptive weight method is integrated to MPC. The future position error through the controller is selected as the driving situation index. The method changes the weight of the performance index depending on the predicted states in online. Finally, adaptive weight function is optimized through learning using evolutionary strategies. The optimization method based on exploration was utilized to optimize performance index with nonlinear characteristics such as ride comfort and handling stability.

The simulation was conducted on a MATLAB/CarSim environment. The conventional vehicle with front wheel steering and direct yaw moment control, a 4WISD vehicle using constant weights, and a 4WISD vehicle using proposed adaptive weights were compared. The proposed method is verified on double lane change condition, and the simulation results show improvement in path tracking, handling stability, and driving comfort.

Chapter 2. Modeling for path tracking control

This chapter discusses the model of 4WISD vehicles for path tracking control. The relationship between the inputs of the vehicle and the states of path tracking is expressed as the state space equation.

2.1. Lateral vehicle dynamics model

To lessen the complexity of control, the lateral dynamics model of a vehicle in which four wheels operate independently is simplified as a bicycle model, as shown in Figure 2.1. The left and right motions of the wheels are determined by the distribution model in Section 3.5 and 3.6.

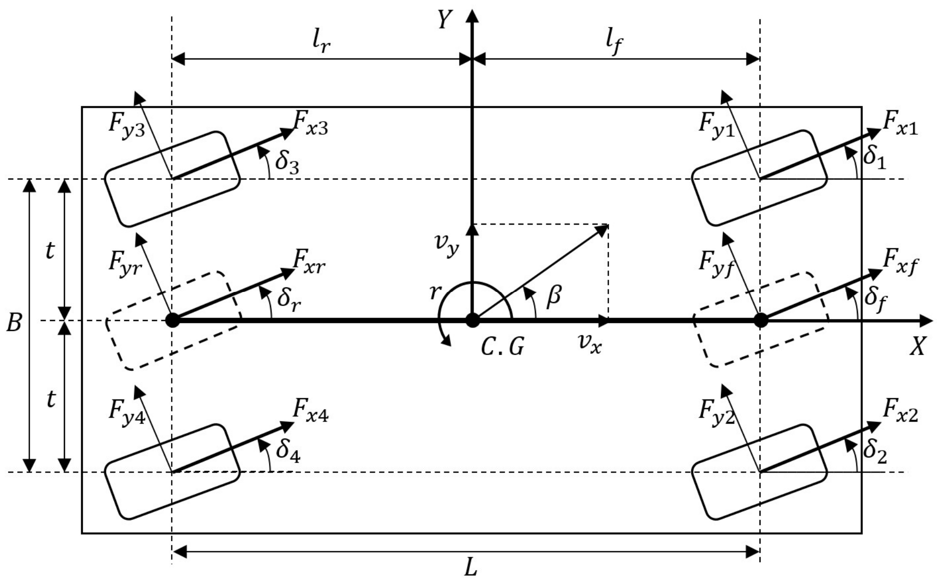


Figure 2.1 Schematic models of 4WISD vehicles

Based on Newton's law, the lateral and yaw dynamics are derived as follows:

$$a_y = \dot{v_y} - v_x\gamma = \frac{1}{m}(F_{yf}cos\delta_f + F_{xf}sin\delta_f + F_{yr}cos\delta_r + F_{xr}sin\delta_r) \tag{2.1}$$

$$\dot{\gamma} = \frac{1}{I_z}\left(l_fF_{yf}cos\delta_f + l_fF_{xf}sin\delta_f - l_rF_{yr}cos\delta_r + l_rF_{xr}sin\delta_r + M_{za}\right) \tag{2.2}$$

M_{za} is additional yaw moment generated by the difference in driving force of each wheel. Assuming that the steering angle is small, it can be assumed as $cos\delta \approx 1$ and $sin\delta \approx 0$ by the small angle approximation. Hence, Equations (2.1) and (2.2) can be written as

$$a_y = \dot{v_y} - v_x\gamma = \frac{1}{m}(F_{yf} + F_{yr}) \tag{2.3}$$

$$\dot{\gamma} = \frac{1}{I_z}\left(l_fF_{yf} - l_rF_{yr} + M_{za}\right) \tag{2.4}$$

The slip angle is the difference between the steering angle of the tire and the traveling angle of the vehicle which can be defined as

$$\alpha_f = \frac{v_y + l_f\gamma}{v_x} - \delta_f,\ \ \alpha_r = \frac{v_y - l_r\gamma}{v_x} - \delta_r \tag{2.5}$$

By assuming that the slip angle is small, the lateral force of tire has a linear relationship with respect to the tire slip angle. Using the linear tire model, the lateral force of tire can be expressed as

$$\begin{aligned} F_{yf} &= C_f\alpha_f \\ F_{yr} &= C_r\alpha_r \end{aligned} \tag{2.6}$$

By summarizing Equations (2.3) – (2.6), the equations of the dynamics can be rewritten as follows:

$$\dot{v_y} = \left(-\frac{C_f + C_r}{v_x m}\right) v_y + \left(-\frac{C_f l_f + C_r l_r}{v_x m} - v_x\right)\gamma + \left(\frac{C_f}{m}\right)\delta_f + \left(\frac{C_r}{m}\right)\delta_r \tag{2.7}$$

$$\dot{\gamma} = \left(\frac{-C_f l_f + C_r l_r}{v_x I_z}\right) v_y + \left(\frac{-C_f l_f^2 + C_r l_r^2}{v_x I_z}\right)\gamma + \left(\frac{l_f C_f}{I_z}\right)\delta_f - \left(\frac{l_r C_r}{I_z}\right)\delta_r + \frac{M_{za}}{I_z} \tag{2.8}$$

2.2. Path tracking model

Tracking a path means minimizing position and heading angle errors between the vehicle and the target path. For this purpose, the path tracking model has lateral position error e_y and yaw angle error e_ψ and their derivative $\dot{e_y}$, $\dot{e_\psi}$ as states variables and has front steering angle δ_f, rear steering angle δ_r and additional yaw moment M_{za} as input variables. The path tracking controller aims to regulate states. The Figure 2.2 illustrates the path tracking model of a 4WIS vehicle.

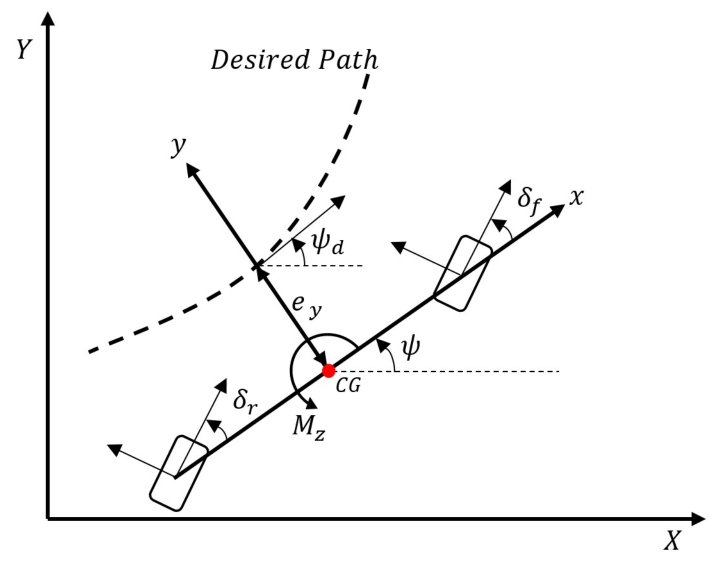


Figure 2.2 Path tracking model of 4WIS vehicles

The yaw angle error and its derivative can be expressed as

$$e_\psi = \psi - \psi_d \tag{2.9}$$

$$\dot{e_\psi} = \dot{\psi} - \dot{\psi_d} = \gamma - \gamma_d = \gamma - v_x\kappa \tag{2.10}$$

The longitudinal velocity is assumed to be constant, and the second derivative of the yaw angle error is expressed as

$$\ddot{e_\psi} = \dot{\gamma} - v_x\dot{\kappa} \tag{2.11}$$

The derivative of the lateral position error $\mathbf{e_y}$ and its second derivative can be derived as

$$\dot{e_y} = \dot{y} - \dot{y_d} = v_y + v_x e_\psi \tag{2.12}$$

$$\ddot{e_y} = \dot{v_y} + v_x\dot{e_\psi} \tag{2.13}$$

Based on Equations (2.7), (2.8), (2.10), and (2.12), Equations (2.13) and (2.11) can be rewritten as

$$\begin{aligned}\ddot{e_y} = &\left(-\frac{C_f + C_r}{v_x m}\right)\dot{e_y} + \left(\frac{C_f + C_r}{m}\right)e_\psi + \left(-\frac{C_f l_f + C_r l_r}{v_x m}\right)\dot{e_\psi} + \left(\frac{C_f}{m}\right)\delta_f \\ &+ \left(\frac{C_r}{m}\right)\delta_r + \left(-\frac{C_f l_f + C_r l_r}{m} - v_x^2\right)\kappa\end{aligned} \tag{2.14}$$

$$\begin{aligned}\ddot{e_\psi} = &\left(\frac{-C_f l_f + C_r l_r}{v_x I_z}\right)\dot{e_y} + \left(\frac{C_f l_f - C_r l_r}{I_z}\right)e_\psi + \left(\frac{-C_f l_f^2 + C_r l_r^2}{v_x I_z}\right)\dot{e_\psi} \\ &+ \left(\frac{l_f C_f}{I_z}\right)\delta_f - \left(\frac{l_r C_r}{I_z}\right)\delta_r + \left(\frac{1}{I_z}\right)M_{za} \\ &+ \left(\frac{-C_f l_f^2 + C_r l_r^2}{I_z}\right)\kappa + (-v_x)\dot{\kappa}\end{aligned} \tag{2.15}$$

Based on Equations (2.10), (2.12), (2.14), and (2.15), the path tracking model can be rewritten in the continuous time−invariant state space model as follows:

$$\begin{gathered} \dot{x(t)} = Ax(t) + Bu(t) + Ew(t) \\ y(t) = Cx(t) + Du(t) \end{gathered} \tag{2.16}$$

where the state vector $x = [e_y \quad \dot{e_y} \quad e_\psi \quad \dot{e_\psi}]^{\mathrm{T}}$, control input vector $u = [\delta_f \quad \delta_r \quad M_{za}]^{\mathrm{T}}$, disturbance vector $w = [\kappa \quad \dot{\kappa}]^{\mathrm{T}}$, and coefficient matrices are given by

$$\begin{gathered} A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & -\dfrac{C_f + C_r}{v_x m} & \dfrac{C_f + C_r}{m} & -\dfrac{C_f l_f + C_r l_r}{v_x m} \\ 0 & 0 & 0 & 1 \\ 0 & \dfrac{-C_f l_f + C_r l_r}{v_x I} & \dfrac{C_f l_f - C_r l_r}{I_z} & \dfrac{-C_f l_f^2 + C_r l_r^2}{v_x I_z} \end{bmatrix} \\ B = \begin{bmatrix} 0 & 0 & 0 \\ \dfrac{k_f}{m} & \dfrac{k_r}{m} & 0 \\ 0 & 0 & 0 \\ \dfrac{l_f k_f}{I_z} & -\dfrac{l_r k_r}{I_z} & \dfrac{1}{I_z} \end{bmatrix}, C = [I]_{4\times4}, D = [0]_{4\times3} \\ E = \begin{bmatrix} 0 & 0 \\ -\dfrac{C_f l_f + C_r l_r}{m} - v_x^2 & 0 \\ 0 & 0 \\ \dfrac{-C_f l_f^2 + C_r l_r^2}{I_z} & -v_x \end{bmatrix} \end{gathered} \tag{2.17}$$

Chapter 3. Control

This chapter describes the path tracking control method of 4WISD vehicles. The overall control scheme is explained in Section 3.1. Sections 3.2 and 3.3 illustrate path tracking control using MPC and the adaptive weight strategy applied to MPC. Sections 3.5 and 3.6 show distribution models for four−wheel independent operating.

3.1. Overall control scheme

Figure 3.1 presents the proposed overall control scheme. States errors are obtained from the target path information, delivered to the path tracking controller. The front and rear steering angles and additional yaw moment are determined through the controller.

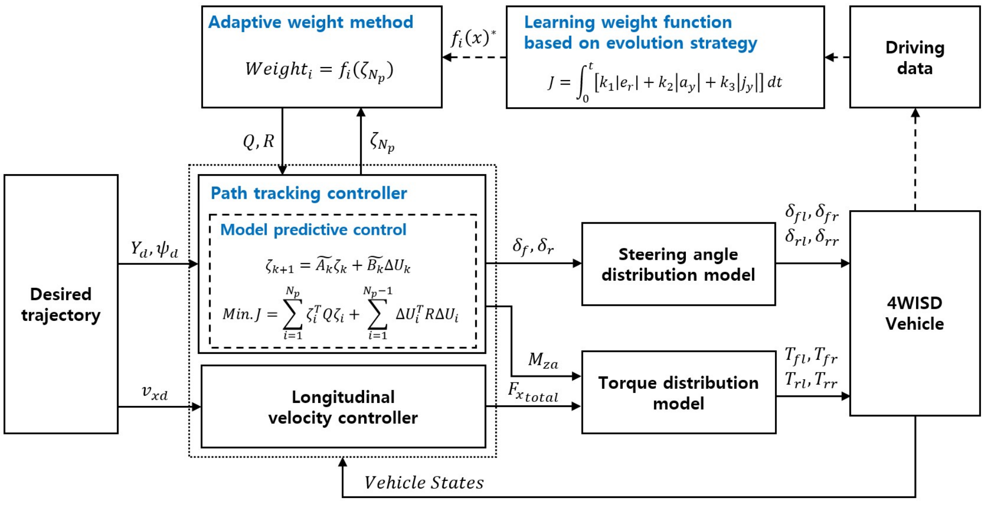


Figure 3.1 Overall control scheme

The longitudinal velocity controller utilizes a velocity error to obtain the total longitudinal force using a proportional–integral–derivative (PID) controller. The torque distribution model distributes the longitudinal force of each wheel to maintain the additional yaw moment and total longitudinal force using quadratic programming. The steering angle distribution model distributes each angle according to the Ackerman steering geometric relationship. The steering angle and drive torque to each wheel are transmitted to the CarSim vehicle model, and the measured states of the vehicle are added to the input feedback of the path tracking controller. The proposed adaptive weight strategy and path tracking controller operate online, exchanging predicted future states and modified weight values. Furthermore, the adaptive weight function is optimized through learning using evolution strategy. Chapter 4 discusses the details of the optimization method.

3.2. Path tracking control

In this study, a path tracking controller is designed using MPC. MPC is a control method using the receding horizon. MPC employs the first input obtained by solving a constrained optimal problem for a finite horizon length, and repeating this process while receding horizon. By solving the optimal problem with constraints every time step, the constraints can be considered in the control. Consequently, using MPC in this study, path tracking performance such as lateral position and heading angle errors can be guaranteed by state constraint conditions. In addition, the control inputs considering the limitations of the actuator can be obtained through the input constraint condition.

To design the model predictive controller, a continuous state space form in Equation (2.17) is converted into a discrete state space form using the zero−order hold method with sampling time Δt. The discrete state space equation is expressed as follows:

$$\begin{aligned} x_{k+1} &= A_d x_k + B_d u_k + E_d w_k \\ y_{k+1} &= C_d x_k + D_d u_k \end{aligned} \tag{3.1}$$

The augmented state vector ζ_k is defined with x_k and u_{k-1}, and new input vector is defined as Δu_k. Hence, the augmented discrete state space model can be expressed as

$$\zeta_k = \begin{bmatrix} x_k \\ u_{k-1} \end{bmatrix} \tag{3.2}$$

$$\begin{gathered} \zeta_{k+1} = \widetilde{A_d}\zeta_k + \widetilde{B_d}\Delta u_k + \widetilde{E_d} w_k \\ y_{k+1} = \widetilde{C_d}\zeta_k + \widetilde{D_d}\Delta u_k \\ \widetilde{A_d} = \begin{bmatrix} A_d & B_d \\ 0_{3x4} & I_{3x3} \end{bmatrix}, \quad \widetilde{B_d} = \begin{bmatrix} B_d \\ I_{3x3} \end{bmatrix}, \quad \widetilde{E_d} = \begin{bmatrix} E_d \\ 0_{3x2} \end{bmatrix} \\ \widetilde{C_d} = [C_d \quad 0_{2x3}], \quad \widetilde{D_d} = [D_d], \end{gathered} \tag{3.3}$$

Using the augmented discrete state space equation, the steering angle rate and additional yaw moment rate are the input vectors and the steering angle and additional yaw moment are the state vectors. Accordingly, a feasible input range and a change rate of the actuators can be considered in the control.

The optimal problem of MPC is defined as follows. As shown in

Equation (3.3), the curvature information of the path is regarded as disturbance. A nominal MPC problem is defined using a zero steady−state model excluding disturbance in Equation (3.4), and a nominal control input is obtained for horizon length using the nominal MPC model.

$$\begin{aligned} \zeta_{k+1} &= \widetilde{A_d}\zeta_k + \widetilde{B_d}\Delta u_k \\ y_{k+1} &= \widetilde{C_d}\zeta_k + \widetilde{D_d}\Delta u_k \end{aligned} \tag{3.4}$$

The net control input is obtained by adding the feedback term $k(w_k)$ to nominal optimal input at each time for disturbance rejection.

The net control input is expressed as follow:

$$u(k) = u^*_{0|k} + k(w_k) \tag{3.5}$$

The performance index for model predictive controller is defined as

$$J_k(\zeta_k, \Delta U_k) = \sum_{i=1}^{N_p} \zeta^T_{i|k} Q_k \zeta_{i|k} + \sum_{i=0}^{N_p-1} \Delta u^T_{i|k} R_k \Delta u_{i|k} \tag{3.6}$$

where Q_k and R_k are diagonal matrices, Q_k is a positive semidefinite matrix and R_k is a positive definite matrix. These weight matrices affect the performance index; hence, they are modified at each time step according to the adaptive weight strategy.

The constraints are considered when solving the optimal control problem. For instance, the physical operating limits of the steering actuator and drive motor create constraints on the input. In addition, constraints on state variables are selected to secure efficient path tracking performance. Moreover, the termination constraint condition is selected to guarantee the feasibility of the model predictive controller.

The nominal optimization problem of MPC can be expressed as follows:

$$\min_{\Delta U_k} J_k(\zeta_k, \Delta U_k) \tag{3.7}$$

subject to

$$\zeta_{i|k} = \widetilde{A_d}\zeta_{i-1|k} + \widetilde{B_d}\Delta u_{i-1|k}$$

$$e_{y_{min}} \le e_{y_{i|k}} \le e_{y_{max}}$$

$$\dot{e}_{\psi_{min}} \le \dot{e}_{\psi_{i|k}} \le \dot{e}_{\psi_{max}}$$

where $i = 1,2,\dots,N_p$

$$\delta_{min} \le \delta_{f_{i|k}} \le \delta_{max}$$

$$\delta_{min} \le \delta_{r_{i|k}} \le \delta_{max}$$

$$\Delta\delta_{min} \le \Delta\delta_{f_{i|k}} \le \Delta\delta_{max}$$

$$\Delta\delta_{min} \le \Delta\delta_{r_{i|k}} \le \Delta\delta_{max}$$

$$\Delta M_{za_{min}} \le \Delta M_{za_{i|k}} \le \Delta M_{za_{max}}$$

where $i = 0,1,2,\dots,N_p - 1$

$$e_{yf_{min}} \le e_{y_{N_p|k}} \le e_{yf_{max}}$$

$$\dot{e}_{yf_{min}} \le \dot{e}_{y_{N_p|k}} \le \dot{e}_{yf_{max}}$$

$$e_{\psi f_{min}} \le e_{\psi_{N_p|k}} \le e_{\psi f_{max}}$$

$$\dot{e}_{\psi f_{min}} \le \dot{e}_{\psi_{N_p|k}} \le \dot{e}_{\psi f_{max}}$$

For each time k, an optimal control input sequence $\Delta U_k^* = [\Delta u_{0|k}^*, \Delta u_{1|k}^*, \dots, \Delta u_{N_p-1|k}^*]$ that satisfies the constraint conditions is obtained by a quadratic programming function on MATLAB.

At time k, the optimal control input $u_{0|k}^{*}$ to be applied to the vehicle is defined as follows:

$$u_{0|k}^{*} = u(k-1) + \Delta u_{0|k}^{*} \tag{3.8}$$

The feedback term for disturbance rejection in Equation (3.5) is defined as follows:

$$k(w_k) = -\widetilde{B_d}^{-1}\widetilde{E_d}w_k \tag{3.9}$$

Net control input is expressed as follows.

$$u(k) = u(k-1) + \Delta u_{0|k}^{*} - \widetilde{B_d}^{-1}\widetilde{E_d}w_k \tag{3.10}$$

3.3. Adaptive weight strategy of model predictive control

As shown in Equation (3.6), weight vectors Q and R affect performance index. Generally, large Q values quickly converge the state to zero and large R reduces the control input, causing the state to converge slowly to zero. However, there is no apparent method for choosing the exact values of these weight vectors.

In the path tracking controller of 4WISD vehicles, each weight matrix has a critical function. For instance, each factor of R determines driving modes such as front or rear wheel steering and size of yaw moment control, and each factor of Q determines the priority of multi−object performance such as tracking performance, handling stability, and driving comfort. For this purpose, the adaptive weight strategy is proposed. This method adjusts the weight matrix according to the driving condition. First, for the driving state index (SI), the adaptive weight is precisely expressed as various SIs are considered, but the increasing number of variables causes a curse of dimensionality problem, which increases the amount of computation exponentially. Therefore, it is good for the SI to have various physical meanings while represented by as few variables as possible. In this study, the future lateral position error is selected as the SI with one variable and can be expressed as

$$\widehat{e_y}(t+\Delta t) = e_y(t) + \dot{e_y}(t)\Delta t = e_y(t) + (v_x(t) + v_y(t)e_\psi(t))\Delta t \tag{3.11}$$

As shown in Equation (3.11), the future lateral position error contains lateral position and yaw angle errors and lateral and longitudinal velocities. The future lateral position error is expected to be effective in determining the behavior of the vehicle because the changes in the four states are reflected. However, the above expression presupposes that the value of each state variable is maintained and Δt should be sufficiently small. In this study, a novel method is proposed for accurate representation of future states for SI. Further, the lateral position error of the predictive states of MPC is selected as the SI. At time k, $\mathrm{Q_k}$ and $\mathrm{R_k}$ weight matrices can be expressed as follows.

$$\begin{gathered} \mathrm{Q_k} = \mathrm{diag}\left(\mathrm{w_{1|k}}, \mathrm{w_{2|k}}, \mathrm{w_{3|k}}, \mathrm{w_{4|k}}\right) \\ \mathrm{R_k} = \mathrm{diag}(\mathrm{w_{5|k}}, \mathrm{w_{6|k}}, \mathrm{w_{7|k}}) \\ \text{where } \mathrm{w_{i|k}} = f_i\left(e_{y(N_p|k-1)}\right) \;\; (i = 1,2,\dots,7) \end{gathered} \tag{3.12}$$

As shown in Figure 3.2, The performance index J_k is modified according to the SI every time step by obtaining the weight matrix at time k based on the expected error of the weight matrix at time $k-1$. Since the modification is based on future position error, intuitively, increasing the Q matrix can compensate more actively if the vehicle's future position error increases even with optimal control, and decreasing R matrix can enhance ride comfort when the future states are considered stable enough.

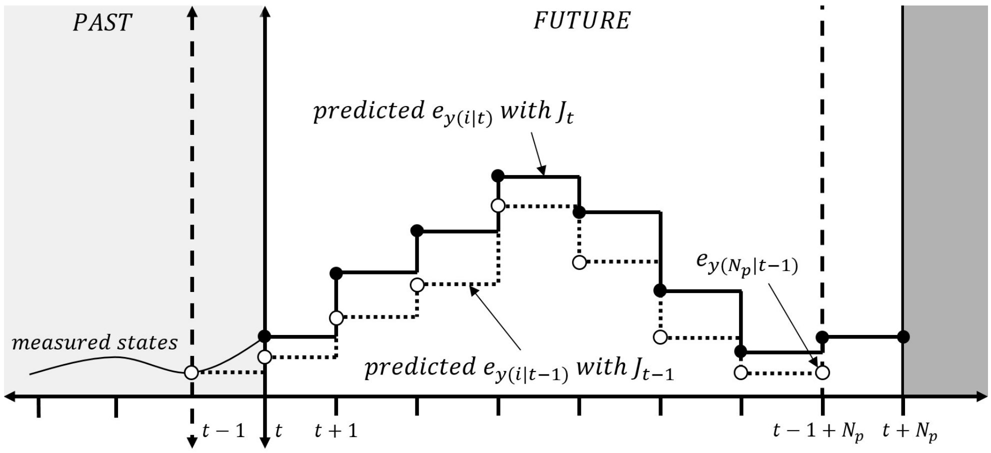


Figure 3.2 Updated performance index based on SI

Secondly, the adaptive weight function $f_i(x)$ can be expressed in various forms, but it is assumed to be linear in this study. After several simulations, linear function is considered the appropriate form. Finally, adaptive weight function can be defined as follows

$$w_{i|k} = a_i(SI_k) + \mathrm{b}_i, \qquad (i = 1,2, \dots ,7) \tag{3.13}$$

In the optimization process of the coefficient a_i, b_i, the SI has a limited range by state constraint; hence, it is easy to add constraint to the algorithm that the weight matrix becomes positive definite.

3.4. Longitudinal velocity control

In the longitudinal velocity control, the required total longitudinal force is obtained using the difference between the target velocity and the current velocity of the vehicle, as shown in Equation (3.14). The total longitudinal force is used as a constraint to obtain the force of each wheel in the driving torque distribution model.

$$F_{x_{total}} = k_P(v_{xd} - v_x) + k_I \int (v_{xd} - v_x) + k_D(\dot{v_{xd}} - \dot{v_x}) \tag{3.14}$$

3.5. Steering angle distribution model

The distribution of the steering angle is based on the Ackermann steering geometry. The center of the turning circle can be obtained from the front and rear wheel steering angles of the bicycle model. The steering angle of each wheel satisfying the Ackermann relationship can be derived as follows:

$$\begin{aligned} \delta_{fl} &= \operatorname{atan}\left(\frac{\tan\delta_f}{1 - \frac{t}{L}(\tan\delta_f - \tan\delta_r)}\right), \delta_{fr} = \operatorname{atan}\left(\frac{tan\,\delta_f}{1 + \frac{t}{L}(\tan\delta_f - \tan\delta_r)}\right) \\ \delta_{rf} &= \operatorname{atan}\left(\frac{\tan\delta_r}{1 - \frac{t}{L}(\tan\delta_f - \tan\delta_r)}\right), \delta_{rl} = \operatorname{atan}\left(\frac{\tan\delta_r}{1 + \frac{t}{L}(\tan\delta_f - \tan\delta_r)}\right) \end{aligned} \tag{3.15}$$

3.6. Driving torque distribution model

In this section, a method for distributing the driving force of each wheel to achieve the required moment and total longitudinal required force is described. The driving force of each wheel F_{xi} satisfies the following equation:

$$F_{x_{total}} = F_{x1}cos(\delta_1) + F_{x2}cos(\delta_2) + F_{x3}cos(\delta_3) + F_{x4}cos(\delta_4) \tag{3.16}$$

$$M_{za} = F_{x1}\left(l_f \sin(\delta_1) - tcos(\delta_1)\right) + F_{x2}\left(l_f \sin(\delta_2) + tcos(\delta_2)\right) + F_{x3}\left(-l_r \sin(\delta_3) - tcos(\delta_3)\right) + F_{x4}(-l_r \sin(\delta_4) + tcos(\delta_4)) \tag{3.17}$$

The drive torque of each tire can be simplified as

$$T_{di} = F_{xi}R_w \tag{3.18}$$

The longitudinal force is distributed to include the margin of the friction cycle of each tire. The relationship between the lateral, longitudinal, and vertical forces of the tire according to the friction cycle is expressed as follows:

$${F_{xi}}^2 + {F_{yi}}^2 \leq \ (\mu F_{zi})^2 \tag{3.19}$$

The optimal problem can be defined as a performance index with a quadratic form while satisfying the constraints

$$\begin{gathered} min.\ x^T Q x \\ subject\ to.\ Ax = b \end{gathered} \tag{3.20}$$

At this time, each matrix is as follows:

$$x = [F_{x1} \quad F_{x2} \quad F_{x3} \quad F_{x4}]^T \tag{3.21}$$

$$Q = diag\left(\frac{1}{(\mu F_{z1})^2 - {F_{y1}}^2}, \frac{1}{(\mu F_{z2})^2 - {F_{y2}}^2}, \frac{1}{(\mu F_{z3})^2 - {F_{y3}}^2}, \frac{1}{(\mu F_{z4})^2 - {F_{y4}}^2}\right) \tag{3.22}$$

$$A^T = \begin{bmatrix} cos\delta_1 & l_f \sin\delta_1 - tcos\delta_1 \\ cos\delta_2 & l_f \sin\delta_2 + tcos\delta_2 \\ cos\delta_3 & -l_r \sin\delta_3 - tcos\delta_3 \\ cos\delta_4 & -l_r \sin\delta_4 + tcos\delta_4 \end{bmatrix}, \qquad b = \begin{bmatrix} F_{x_{total}} \\ M_{za} \end{bmatrix} \tag{3.23}$$

Using the Lagrange multiplier λ, the Hamiltonian is defined as

$$H = [x^T Q x] + \lambda[Ax - B] \tag{3.24}$$

The necessary conditions are as follows:

$$\frac{\sigma L}{\sigma x} = x^T Q + \lambda A = 0 \tag{3.25}$$

$$\frac{\sigma L}{\sigma \lambda} = Ax - b = 0 \tag{3.26}$$

Based on Equation (3.25), Equation (3.26) is rewritten as follows:

$$x^T = -\lambda A Q^{-1} \qquad x = -Q^{-1} A^T \lambda^T \tag{3.27}$$

$$A(-Q^{-1} A^T \lambda^T) - b = 0 \qquad \lambda^T = (-AQ^{-1}A^T)^{-1} b \tag{3.28}$$

In summary, the driving force of each wheel can be obtained as follows:

$$x = Q^{-1} A^T (AQ^{-1} A^T)^{-1} b \tag{3.29}$$

Chapter 4. Optimization of Adaptive Weight Function

In this chapter, the optimization method using the evolutionary strategy is proposed. Considering the purpose of the autonomous vehicle, the overall performance should include various indices, i.e., not only path tracking performance such as position error and handling stability but also ride comfort. Moreover, an improvement of path tracking performance does not mean an improvement of ride comfort of the vehicle.

To optimize the overall performance of the vehicle, this study aims to maximize the handling stability and ride comfort within a certain level of lateral position error. Since the path tracking performance is guaranteed under the state constraint of the MPC, the fitness function of the adaptive weight function optimization problem is defined to minimize lateral acceleration, lateral jerk and yaw rate error to achieve ride comfort and handling stability.

The fitness function is defined as follows:

$$F = F_{er} + F_{ay} + F_{jy} = \int_0^t \left[k_1|e_r| + k_2|a_y| + k_3|j_y|\right] dt \tag{4.1}$$

4.1. Evolution strategy

An evolution strategy algorithm is applied to obtain the coefficient of adaptive weight function that minimizes the fitness function. The above fitness function is a multimodal function that includes a factor with nonlinear characteristics of a vehicle and a term that expresses the factor in different forms. Therefore, it is difficult to predict the properties of the fitness function such as convexity, continuity, and ruggedness. In this study, the method using evolution strategy is selected for the black box optimization problem. The evolution strategy not only reliably find global solutions but also have the following advantages of computing time. The crossover step of the general genetic algorithm was omitted and the computation was reduced. Parallel computing is possible because the results of each search point are independent of calculating the fitness score. In this paper, the computing time can be reduced through parallel simulation. By applying methods such as elite evolution strategy and covariance matrix adaptation evolution strategy, the convergence rate increased.

In general, optimization by exploration is not guaranteed to be stable as it explores unknown areas. However, in this study, the essential performances, such as tracking performance and handling stability, are guaranteed with MPC, and the ancillary performance, such as ride comfort, is optimized using the evolution strategy method. This approach enables optimization while maintaining safety during driving.

4.2. Optimization algorithm based on evolution strategy

In this study, general ES is modified according to the purpose of optimizing the weight matrix. Since the performance index is affected the relative size of the weights, the ratio is more important than the size of the value. Therefore, the method of multiplying the noise by the optimization process is applied. And the coefficients of adaptive weight function are constrained so that the weight vector are positive.

In addition, Elite ES method and adaptive variance is applied the proposed algorithm to increase the convergence rate.

The algorithm is expressed as shown in Figure 4.1

Initialize mean parameter (m_n), parameters set ($\theta_{n\times(\lambda-\mu)}$), Elite parameter set ($E_{n\times\mu}$)
Initialize variance (V_n)
repeat
Sample noise matrix ($e_{n\times(\lambda-\mu)} \sim N(1, V_n)$)
  if e_{i*n} has negative **then** resample ($e_{n\times(\lambda-\mu)} > 0$)
  end if
Create parameter set ($\theta_{n\times\lambda} = m_n * e_{n\times(\lambda-\mu)} + E_{n\times\mu}$)
Evaluate fitness score (F_λ) by simulation
Sort parameter set ($\theta_{n\times\lambda}$) in the order of descent
Update Elite parameter set ($E_{n\times\mu}$)
Update variance ($V_n = Var(e_{n\times\mu})$)
Update mean parameter $m_n^{k+1} = m_n^k * (\sum_j^s F_\mu e_{n\times\mu})$
until $\theta_{k+1} - \theta_k < \epsilon$

Figure 4.1 Proposed evolution strategy algorithm

To apply the above algorithm to an MPC using a constant weight, the value of parameter matrix corresponding to a_i in Equation (3.13) is set to zero.

Chapter 5. Simulation

In this chapter, the simulation conditions and results are described. The simulation results of the conventional models are confirmed to compare the performance of the adaptive weight MPC. The first model is a front−wheel steering and four−wheel drive vehicle, which uses a method of steering the front wheel and assisting yaw rate control through the driving force. The Stanley method is used as the steering method for path tracking. The second model is a four−wheel steering and four−wheel drive vehicle, which uses a method of applying a general MPC with a constant weight. The weight matrix is optimized using the evolutionary strategy algorithm as discussed in Chapter 4. The last model uses the method of applying the adaptive weight MPC. The coefficients of the adaptive functions were optimized using the evolutionary strategy algorithm. By comparing the above three cases, the results of path tracking control, adaptive weight characteristic, and optimization process by evolution strategy are explained. The simulation is conducted on a MATLAB/CarSim environment.

5.1. Simulation Condition

To obtain test vehicle data, the specifications of the self−driving shuttle are considered. The self−driving shuttle is expected to be the first fully autonomous driving vehicle, and the application of various steering modes, such as lateral parking and 360 degree rotating, of four−wheel independent steering is also advantageous. The self−driving shuttle repeats a driving given route with a similar speed. The characteristic of autonomous shuttles is appropriate for learning based on evolution strategy by repeatedly performing under similar conditions. The test environment is assumed as a double−lane change (DLC). The DLC conditions are suitable for evaluating the path tracking performance and lateral dynamics of a vehicle. The specifications of the vehicle are as shown in Table 5.1.

Table 5.2 presents the parameters of the MPC controller. The sampling time is 0.05 s and the predictive and control horizons are set as 30. The state constraints are set as $e_{y_{max}} = 0.06\ m, e_{y_{min}} = -0.06\ m, \dot{e}_{\psi_{max}} = 0.1\ rad, \dot{e}_{\psi_{min}} = -0.1\ rad, \delta_{max} = 1.57\ rad, \delta_{min} = -1.57\ rad$. The control input constraint is set as $\Delta\delta_{max} = 0.052\ rad, \Delta\delta_{min} = -0.052\ rad, \Delta M_{za_{max}} = 1000\ \mathrm{Nm}, \Delta M_{za_{min}} = -1000\ \mathrm{Nm}$. The terminal constraint is set as $e_{yf_{max}} = 0.03\ m, e_{yf_{min}} = -0.03\ \mathrm{m}, \dot{e}_{yf_{max}} = 0.01\ m/s, \dot{e}_{yf_{min}} = 0.01\ m/s, e_{\psi f_{max}} = 0.01\ rad, e_{\psi f_{min}} = -0.01\ \mathrm{rad}, \dot{e}_{\psi f_{max}} = 0.01\ rad/s, \dot{e}_{\psi f_{min}} = 0.01\ rad/s$.

Parameters	Symbol	Unit	Value
Mass of vehicle	m	kg	3400
Moment of inertia	I_z	kgm^2	4000
Front wheel base	l_f	m	1.6
Rear wheel base	l_r	m	2.0
Wheel base	l	m	3.6
Track	B	m	2.0
Front rire cornerring stiffness	C_f	N/rad	3000
Rear tire cornerring stiffness	C_r	N/rad	3000
Target longitudinal velcoity	v_{xd}	km/h	50

Table 5.1. Data of a vehicle

Parameters	Symbol	Unit	Value
Sampling time	Δt	sec	0.05
Predictive horizon	N_p	–	30
Contorl horizon	N_c	–	30
Constraint of lateral postion error	$e_{y_{max}}, e_{y_{min}}$	m	± 0.06
Constraintof yaw rate error	$e_{\dot{\psi}_{max}}, e_{\dot{\psi}_{min}}$	rad/s	± 0.10
Constraint of steering angle	$\delta_{max}, \delta_{min}$	rad	± 1.57
Constraint of steering angle rate	$\Delta\delta_{max}, \Delta\delta_{min}$	rad	± 0.052
Constraint of additional yaw moment rate	$\Delta M_{za_{max}}, \Delta M_{za_{min}}$	Nm	± 1000
Terminal constraint of lateral postion error	$e_{yf_{max}}, e_{yf_{min}}$	m	± 0.03
Terminal constraint of yaw angle error	$e_{\dot{y}f_{max}} e_{\dot{y}f_{min}}$	m/s	± 0.01
Terminal constraint of lateral postion error	$e_{\psi f_{max}}, e_{\psi f_{min}}$	rad	± 0.01
Terminal constraint of yaw angle error	$e_{\dot{\psi} f_{max}}, e_{\dot{\psi} f_{min}}$	rad/s	± 0.01

Table 5.2. Parameters of model predictive control

5.2. Learning result of optimization progress

The optimization process is conducted to check that the proposed method adequately finds the solution. Optimization using the evolutionary strategy was performed for two cases: constant weight method and adaptive weight method. The average and 95% confidence intervals of each step are displayed. The result is obtained by 15 repetitions under the same initial conditions for each case. Table 5.3 displays the coefficients of the initial weight function.

Symbol	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Value	0	0	0	0	0	0	0
Symbol	b_1	b_2	b_3	b_4	b_5	b_6	b_7
Value	1	1	1	1	3	3	$1e-8$

Table 5.3 Coefficients of initial weight function

The parameters of the evolutionary strategy are as Table 5.4.

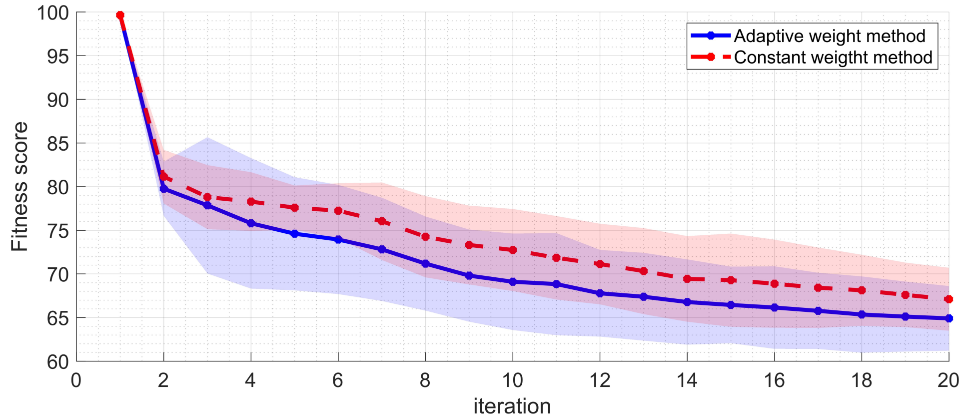
Parameters	**Symbol**	**Value**
Number of samples	λ	30
Elitist	μ	5
Initial variance	V	1.0
Step size	σ	1
Coefficient of object function	k_i	[5,3,2]

Table 5.4 Coefficients of evolution strategy

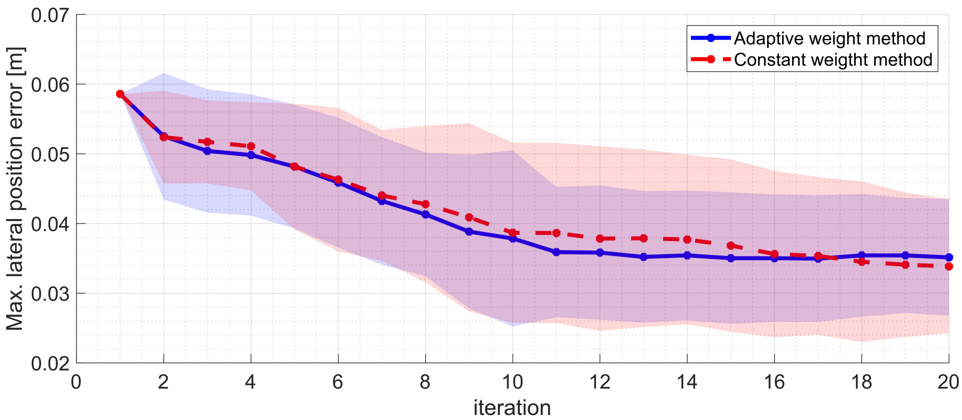
Figure 5.1 displays the optimization results. The fitness function converged within 20 generations. The value of the fitness function converged to 67.1 for the constant weight method and to 64.9 for the adaptive weight method. Owing to the evolutionary strategy characteristic of random searching by a Gaussian distribution, the steps implied that the score is reversed in the optimization process, but the score of the adaptive weight method is lower than that of the constant weight method overall. In the case of a lateral position error, the final convergence values are 3.4 cm and 3.5 cm, respectively, which are similar. the convergence values were achieved within 6 cm, which was selected from the state constraint of the MPC. The yaw rate converges to 0.029 rad/s and 0.022 rad/s, respectively, and the adaptive weight method is more advantageous. In the case of lateral acceleration and jerk, the constant weight method converges to 0.568 G and 2.897 G/s and the adaptive weight method converges to 0.552 G and 2.701 G/s; hence, the adaptive weight method is ~0.016 G, ~0.196 G/s better, respectively. The yaw rate, lateral acceleration and lateral jerk are included in the fitness function, and the adaptive weight method showed better results than the constant weight method. For optimizing ride comfort and handling stability while ensuring lateral position error, the adaptive weight method showed relatively more advantageous results.

Model	Constant weight method	Adaptive weight method
Max. Lateral positon Error (m)	0.034	0.035
Max. Yaw rate error (rad/s)	0.029	0.022
Max. Lateral acceleration (G)	0.568	0.552
Max. Lateral jerk (G/s)	2.897	2.701

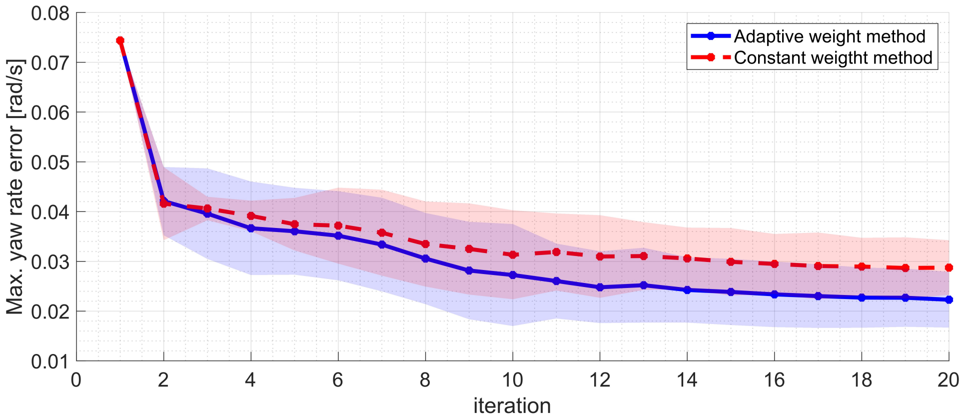
Table 5.5 Average of convergence performance



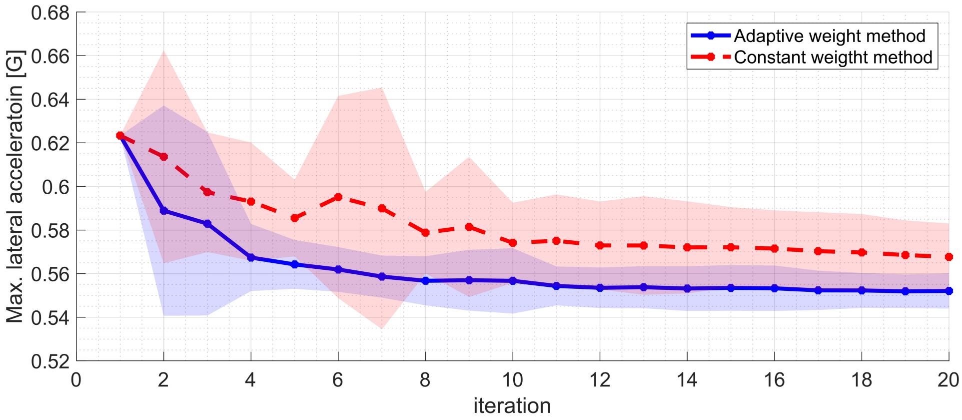
(a) fitness function score



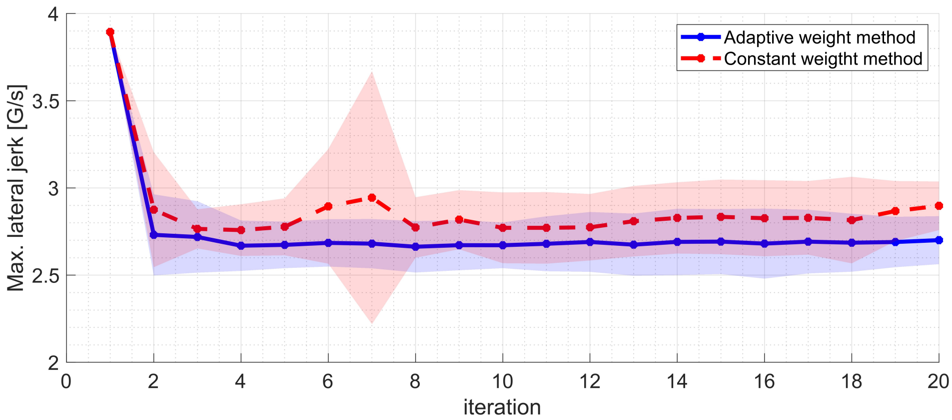
(b) Maximum lateral position error



(c) Maximum yaw rate error



(d) Maximum lateral acceleration



(e) Maximum lateral jerk

Figure 5.1 Result of optimization progress: (a) fitness score, (b) maximum lateral position error, (c) maximum yaw rate error, (d) maximum lateral acceleration, (e) maximum lateral jerk

Based on the simulation results, the optimal coefficient was selected as the minimum fitness score of each type as shown in Table 5.7.

Symbol	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Value	0	0	0	0	0	0	0
Symbol	b_1	b_2	b_3	b_4	b_5	b_6	b_7
Value	7.76	0.17	97.55	251.1	3	20.56	$7.6e-09$

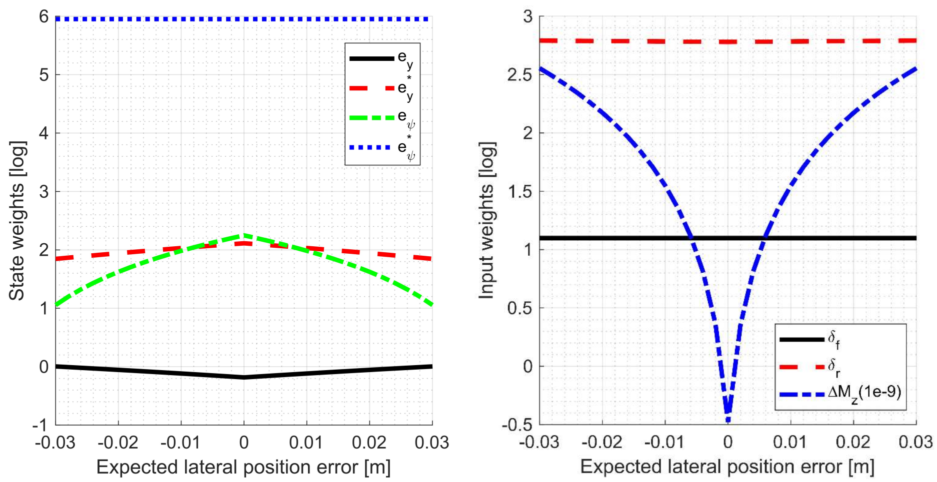
Table 5.6 Optimization result of constant weight function

Symbol	a_1	a_2	a_3	a_4	a_5	a_6	a_7
Value	2.86	−10.76	−109.9	2.49	0	2.97	$4.0e-08$
Symbol	b_1	b_2	b_3	b_4	b_5	b_6	b_7
Value	0.83	8.27	9.47	383.9	3	16.1	$6.2e-09$

Table 5.7 Optimization result of adaptive weight function

The changes in adaptive weight of Table 5.7 are as follows. Figure 5.2 shows the changes in the adaptive weights according to the SI. Among the four state weights, e_y, $\dot{e_y}$ and e_ψ are changed while $\dot{e_\psi}$ maintain high portion of weights independent of the SI. The weight of e_y is increased as the expected position error increases, rapidly reducing the lateral position error. On the contrary, when the expected position error decreases, the weight of $\dot{e_y}$ and e_ψ are increased. This policy reduces lateral acceleration and jerk due to rapid position changes while holding the position error and reducing heading angle error when SI is small, leading to improved ride comfort with minimizing yaw angle error.

In the case of the input, the overall tendency of front wheel steering rather than rear wheel steering can be confirmed. Since the influence of the rear wheel steering angle has a huge impact on the direction of the vehicle body, rear wheel steering operates with a low portion. When the SI increases, a strategy is observed to stabilize the vehicle quickly by increasing the amount of rear steering control. Yaw moment control is operated with a relatively large value when the SI is small. In summary, it was optimized to drive with front wheel steering and yaw moment control when the expected position error is small, and to actively use rear wheel steering when the expected position error increases.



(a) State weights (b) Input weights

Figure 5.2 Changes of adaptive weight by SI:

(a) state weights, (b) input weights

5.3. Predictive states of adaptive weight function

Figure 5.3 shows the simulation result of the SI used in the adaptive weight method. According to the sampling time and predictive horizon shown in Table 5.2, the future predictive state is 1.5 s ahead of the actual state. In other word, the SI indicates the position error 1.5 s later when controlled by the performance index with a constant weight. The SI does not exceed 0.03 m by the terminal constraint. By modifying the performance index using the future position, the adaptive weight strategy improves the performance of model prediction control.

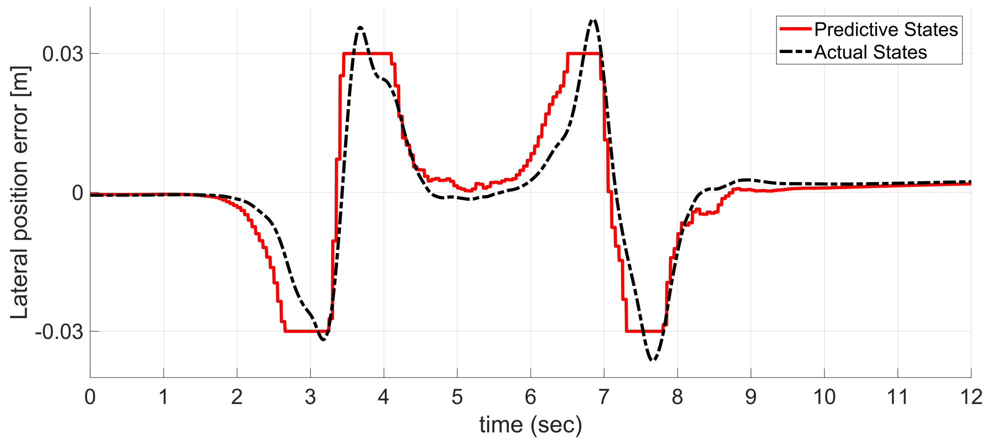


Figure 5.3 Predictive states of lateral position error:

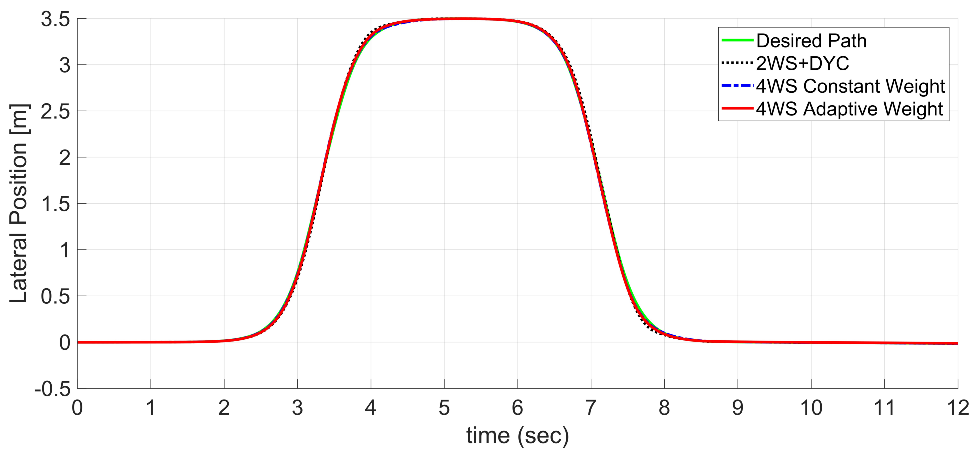
5.4. Comparison Result with Conventional Model

The proposed method is compared with conventional models. Table 5.8 displays the simulation result. The maximum and root mean square (RMS) value of each performance factor are expressed by the model. The 4WIS optimal control with adaptive weight satisfies the criteria of lateral position error and shows the best performance in yaw rate error, lateral acceleration and lateral jerk. Compared to Models 1 and 2, the proposed method improved the maximum yaw rate error by 89% and 48%, and the RMS of lateral acceleration by 4% and 1%, and the RMS of lateral jerk by 4% and 2%, respectively.

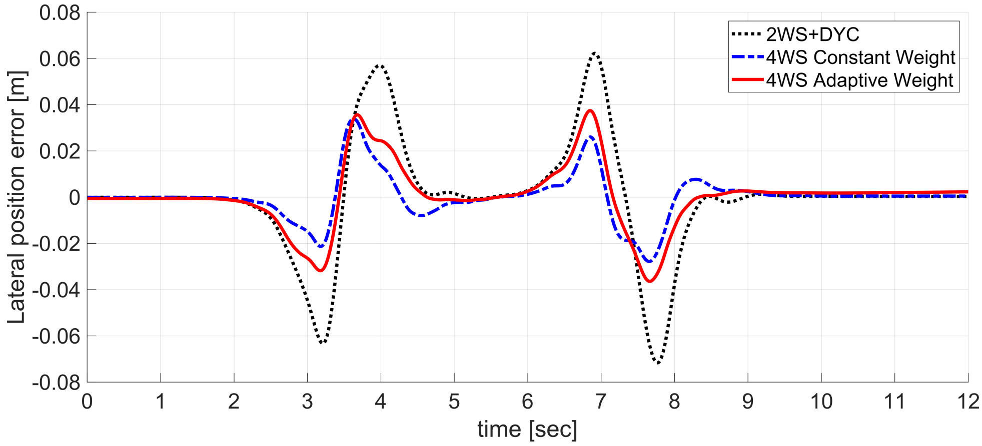
Model		Model 1 (2WS+DYC)	Model 2 (4WS+Const.)	Proposed (4WS+Adapt.)
Lateral positon Error (m)	Max	0.072	0.034	0.037
	RMS	0.021	0.009	0.012
Yaw rate error (rad/s)	Max	0.125	0.027	0.014
	RMS	0.027	0.006	0.003
Lateral acceleration (G)	Max	0.565	0.557	0.548
	RMS	0.190	0.183	0.182
Lateral jerk (G/s)	Max	2.55	3.04	2.57
	RMS	0.61	0.60	0.59

Table 5.8 Path tracking result under double lane change

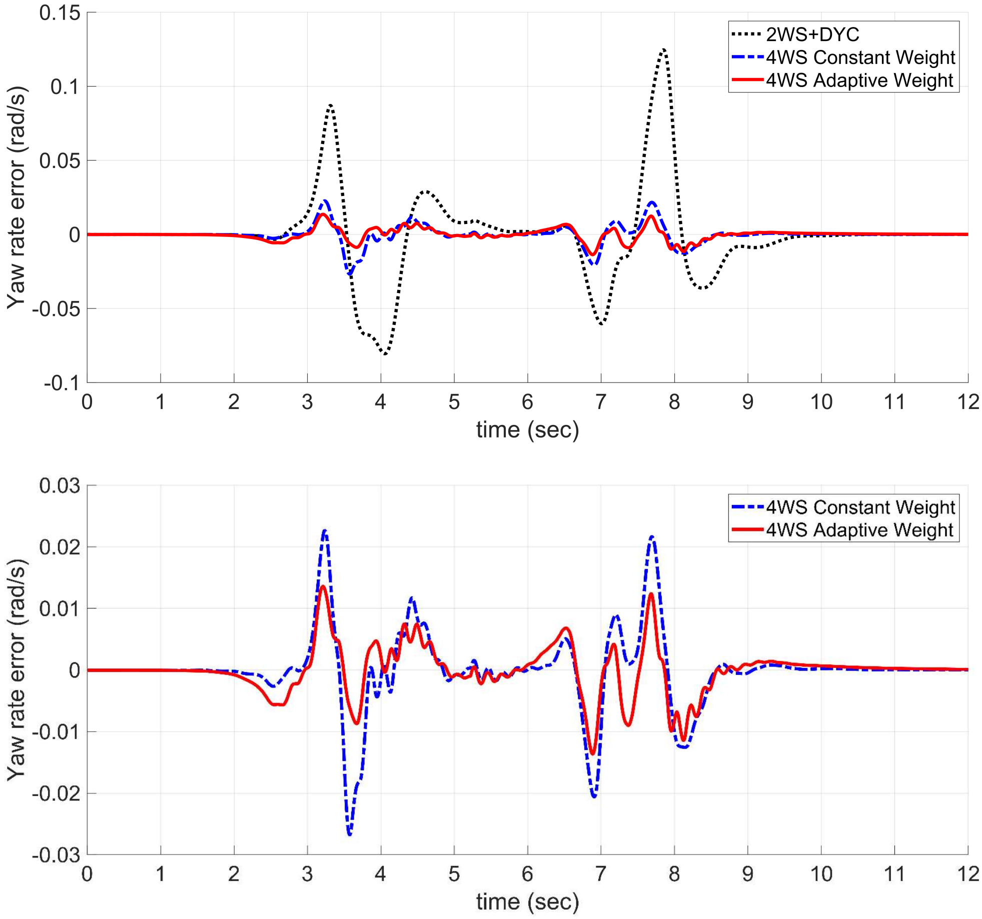
Figures 5.4 and 5.5 show the simulation results, which can be analyzed in two aspects. In the state perspective, the difference between front-wheel steering method and four-wheel steering method was significant because the latter using MPC maintains a small level of lateral position error and yaw rate error. As four-wheel steering became possible, yaw rate error could be easily reduced, which improved path tracking performance such as lateral position error. The adaptive weight method further improves yaw rate error, lateral acceleration and lateral jerk by adjusting weight compared with the constant weight method. For yaw rate error, the adaptive weight method presents a smaller error on the whole than the constant weight method. For lateral acceleration, there was slight improvement in the maximum value of the entire section; however, there is an improvement in the section returning straight path from the curved path around 4 and 8 seconds in Figure 5.4 (d). For this section, the adaptive weight method improved performance by 11% and 3% compared to the conventional models, respectively. Consequently, it was confirmed that the overall performance was improved by controlling four-wheel steering through MPC and the adaptive weight method showed better handling stability and ride comfort while satisfying the path tracking criteria.



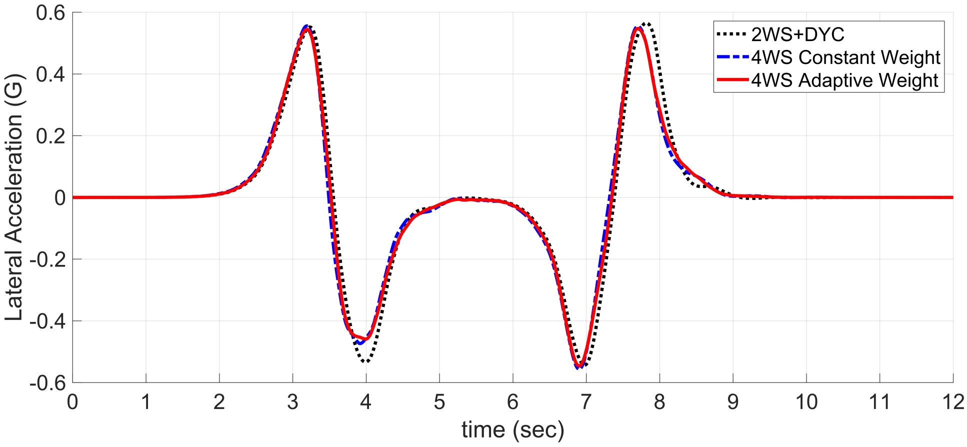
(a) Lateral position



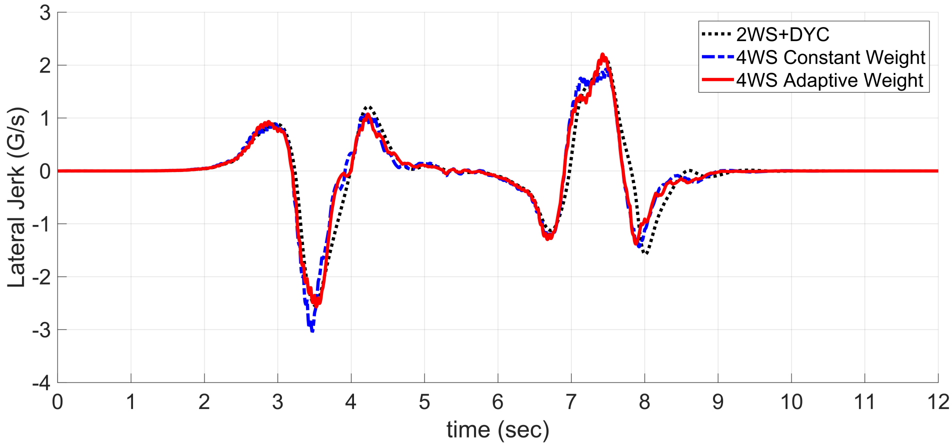
(b) Lateral position error



(c) Yaw rate error



(d) Lateral acceleration

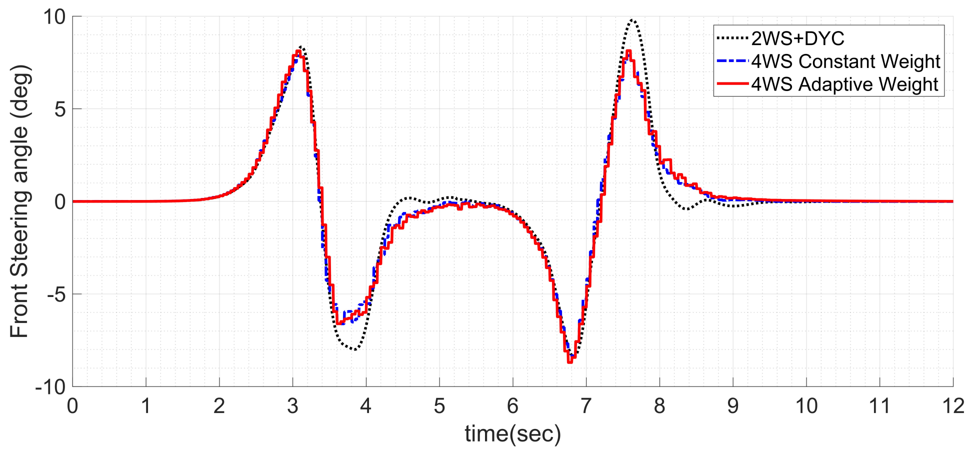


(e) Lateral jerk

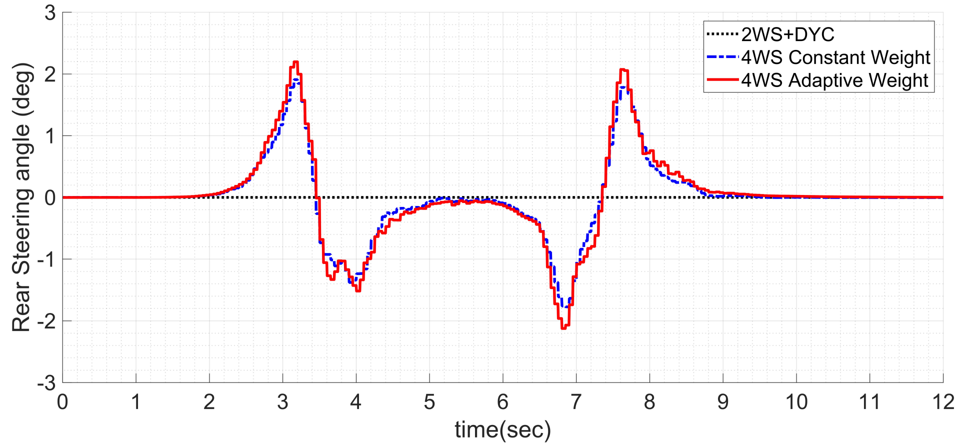
Figure 5.4 Result of path tracking: (a) lateral position,
(b) lateral position error, (c) yaw rate error
(d) lateral acceleration (e) lateral jerk

Figure 5.5 shows the perspective of the control input. The control input is optimized to achieve performance while meeting the constraints. First of all, the four-wheel steering vehicle using MPC performs path tracking by small amount of yaw moment control than the front-wheel steering model because rear wheel steering is additionally used to reduce the yaw rate.

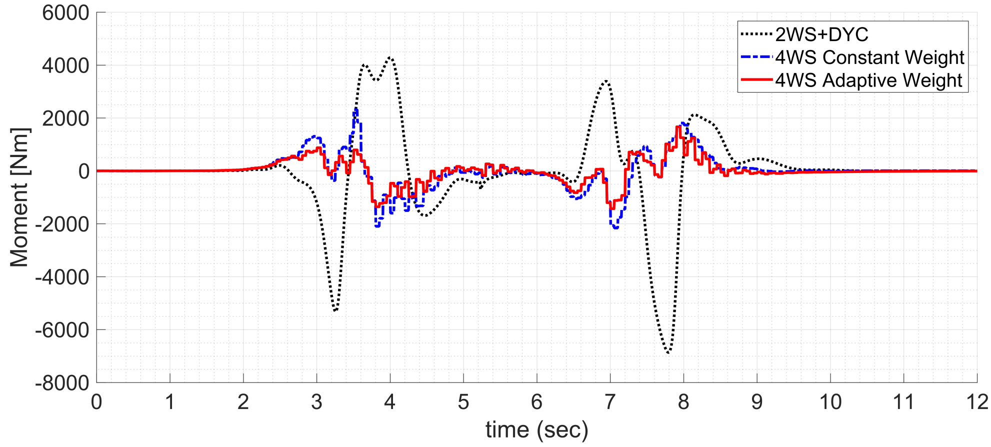
According to the optimization results mentioned in Section 5.2, the adaptive weight method uses the rear wheel steering more actively and reduces the amount of yaw moment control as the SI increases. In the figure 5.5 (b) and (c), it is observed that the adaptive weight method has the same rear wheel steering angle as the constant weight method up to about 2.7 seconds, but after that as the expected position error increases, the rear wheel steering increases and reduces the yaw moment control. Consequently, it is confirmed that the adaptive weight method has a larger rear wheel steering angle and a smaller maximum value of yaw moment control than the constant weight method at large SI. The changes in control inputs of optimization result can also be confirmed in the simulation.



(a) Front steering angle



(b) Rear steering angle



(c) Additional yaw moment

Figure 5.5 Control input of path tracking: (a) front steering angle, (b) rear steering angle, (c) additional yaw moment

Chapter 6. Conclusion

In this study, an optimal path tracking controller is designed for 4WISD vehicles, and an adaptive weight method is proposed to change the weight matrix according to the driving conditions. The path tracking controller is designed using MPC. The predictive states of the MPC are used as parameters of the adaptive weight function. The adaptive weight method improves overall performance and changes the driving mode combination by changing the performance index of the optimal control. An optimization algorithm based on the evolutionary strategy is proposed to find the coefficient of adaptive weight function, which is optimized through learning using MATLAB/CarSim simulations.

In a simulation result, the proposed method achieves improvements in path tracking performance, handling stability, and ride comfort compared with the conventional models.

Through this study, the following conclusions are obtained:

1) The path tracking control of the four-wheel steering vehicle is performed using MPC. Compared to the conventional front-wheel steering vehicle, it was possible to improve the path tracking performance and ride comfort while satisfying the limitation of actuator and constraint of vehicle states. In particular, as control of four wheels became possible, the handling stability was significantly improved.
2) The proposed adaptive weight method for changing the performance index according to the expected position error is effective in improving vehicle performance compared with the

constant weight method. The expected position error is delivered from model predictive controller and a reliable value is obtained without additional computation.

3) The stability and performance of the controller changed significantly according to the weight matrix of the performance index of MPC, which proves the need of an appropriate weight matrix. In this study, the weight matrix is optimized using the evolution strategy, which is confirmed to be a valid method as it stably converges into a global solution.

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Abstract

적응식 가중 행렬 최적 제어에 기반한 사륜 독립 조향 구동 차량의 경로 추종 제어

본 논문에서는 사륜 독립 조향 구동 차량의 경로 추종 제어를 위하여 최적 제어의 성능 함수에 적응식 가중 행렬을 적용한 모델 예측 제어기를 설계하였다. 차량의 종합 성능을 올리기 위하여 주행 환경에 따라 각 성능 우선 순위를 수정하고 주행 모드를 변경하는 전략을 제안하였고, 이는 모델 예측 제어를 통해 예측된 미래 상태에 따라 최적 제어의 성능 함수를 수정하는 방법을 통해 구현되었다. 이를 위해 사륜 독립 조향 구동 차량의 동역학 모델 및 경로 추종 모델을 정의하였으며 이는 모델 예측 제어의 참조 모델로 사용되었다. 모델 예측 제어를 적용하여 경로 추종 제어기를 설계하였고 이 때 상태 구속 조건을 통해 경로 추종 성능을 확보하고 입력 구속 조건을 조향 액츄에이터의 작동 범위과 속도를 반영하였다. 제안된 적응식 가중 행렬 전략은 예상 주행 상태에 따라 성능 함수의 계수를 수정하며 이 때 예상 주행 상태는 모델 예측 제어를 통해 구해진 미래 상태 값을 사용하였다. 마지막으로 적응식 가중 행렬 함수를 진화 전략을 통한 학습을 통해 최적화하였다. 진화 전략의 적합도 함수는 승차감와 같이 경로 추종 제어기에서 고려할 수 없는 차량 상태를 포함할 수 있다. 즉, 모델 예측 제어의 구속 조건과 적응식 가중 행렬 함수 최적화를 이용하여, 횡방향 위치 오차를 일정 기준 이내로 만족시키면서 핸들링 안정성과 승차감을 최대화하는 방법으로 차량의 종합 성능 향상을 구현하였다. 학습과 시뮬레이션은 CarSim/MATLAB 환경에서 수행되었으며 제안된 방법은 전륜 조향

모델과 고정 가중 행렬을 사용한 사륜 조향 모델과 비교하였다. 차량의 종합 성능 개선을 확인하기 위하여 횡방향 위치 오차, 요레이트 오차, 횡방향 가속도와 가가속도값에 대한 검증 결과를 제시하였다.

주요어: 경로 추종 제어, 모델 예측 제어, 적응식 가중 행렬, 진화 전략, 사륜 독립 조향 구동

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