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비젼 기반 자율주행을 위한 다중비율 예측기 설계와 모델예측 기반 능동조향 제어

MPC-based Active Steering Control using Multi-rate Kalman Filter for Autonomous Vehicle Systems with Vision

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Abstract - In this paper, we present model predictive control (MPC) applied to lane keeping system (LKS) based on a vision module. Due to a slow sampling rate of the vision system, the conventional LKS using single rate control may result in uncomfortable steering control rate in a high vehicle speed. By applying MPC using multi-rate Kalman filter to active steering control, the proposed MPC-based active steering control system prevents undesirable saturated steering control command. The effectiveness of the MPC is validated by simulations for the LKS equipped with a camera module having a slow sampling rate on the curved lane with the minimum radius of 250[m] at a vehicle speed of 30[m/s].

Key words : Lane keeping system(LKS), Model predictive control(MPC), Multi-rate system, Steering control, Lane detection

Nomenclature

$\{XYZ\}$: global coordinate frame
$\{xyz\}$: local coordinate frame
x : longitudinal position of the origin of $\{xyz\}$ coordinate to the font fixed point along the longitudinal axis
y : lateral position of the origin of $\{xyz\}$ coordinate to the rotation center 'O' along the lateral axis
V_x : longitudinal velocity of the vehicle at c.g.
ψ : yaw angle
$\dot{\psi}$: yaw rate
β : side slip angle
$e_{yL} = y_L - y_L^d$: lateral position error w.r.t. reference at look-ahead distance
$e_\psi = \psi^d - \psi$: yaw angle error w.r.t. road
C_a : cornering stiffness of tire
I_z : yaw moment of inertia of vehicle
m : total mass of the vehicle
l : distance of the tire respective from c.g. of the vehicle
δ : steer angle
L : look-ahead distance from c.g. to look ahead point
N_P : predictive horizon
N_C : control horizon
Q, R : MPC weighting for states and control command
u : input

Subscripts

f : front
r : rear
L : value at look-ahead distance

Superscripts

d : desired value

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1. INTRODUCTION

The active safety systems have increased in the automotive industry [1-3]. Anti-lock braking system and electronic stability program enhance the vehicle stability by controlling the brake systems effectively. Lane keeping system (LKS) controls the front steer angle in order to improve lateral vehicle stability. Through implementation of the LKS, the steer angle can be assisted by getting the information of road environment and vehicle's states. Moreover, LKS can be implemented for the autonomous vehicle systems by tracking the reference trajectory. The robust switching LKS controller was proposed in [1], where the vehicle has magnetic sensors and it tracks the lane reference with magnetic markers. Recent trends in LKS research are using the vision system to obtain the road information. The lane keeping assistant system

(LKAS) with vision module is also studied with the desired reference path generation algorithm and optimal controller [2]. It was reported that the model based predicted controller for LKAS with a vision module is robust against time delay [3].

For industrial application of vision systems, fast road information measurement is not available due to cost restriction on vision modules. Thus, the slow sampling period and time delay of a camera module compared to the car electronic control unit (ECU) and inertia measurement units (IMU) should be considered in the design of controller. The conventional method for resolving such slow sampling rate and time delay is generating the steer angle at the same period as the measurement period of the vision module. This method, however, leads to an inaccurate solution of the control command, and as a result the vehicle may have undesirable lateral behavior such as oscillatory yaw rate. The previous results[1-3], however, do not consider these problems. For resolving these problems, we propose multi-rate Kalman filter that can estimate the informations of the vision data at the period of the control command. Multi-rate Kalman filter can make optimal signal having the minimum-variance reconstruction based on the probability theory [4],[5].

In this paper, we propose a model predictive control (MPC) for multi-rate LKS. MPC computes a sequence of control inputs to optimize the future behavior under various constraints [6],[7]. The MPC has been applied to active front steering control [8-10]. These papers also do neither consider slow sampling rate nor the camera module's time delay. And performances were evaluated at only low vehicle speeds. In this paper, the MPC is applied to the LKS under the constraints of steer angle and rate. We demonstrate the effectiveness of the proposed multi-rate estimation and control system through simulations based on three scenarios: (1) a slowly controlled system at a slow rate as the vision module. (2) a fast controlled system at each ECU computation instance utilizing a high-speed vision module. (3) the proposed method : multi-rate system with the multi-rate Kalman filter utilizing a slow rate vision module.

Simulation results show that the system using the multi-rate estimator improves lane keeping performance even at high speeds. we confirm that the system using multi-rate estimator with a low cost vision module was competitive performance with the system having the fast vision module.

This paper is structured as follows : Section 2 describes the lateral dynamics of a vehicle. Section 3 describes the multi-rate Kalman filter, the MPC method and control structure of the system. Section 4 shows simulation results under various scenarios.

2. LATERAL DYNAMICS MODEL OF VEHICLE

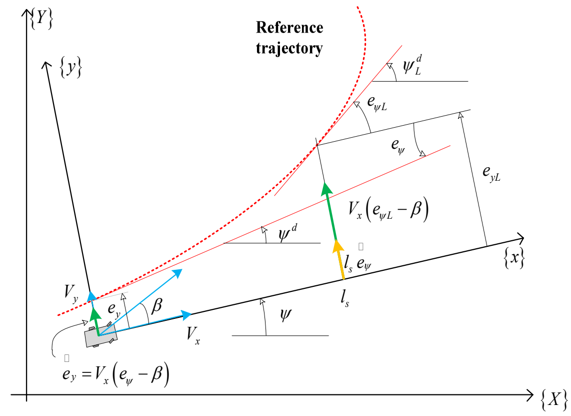


Fig. 1 Lateral vehicle dynamics

The simple bicycle model [11] is used to model the lateral dynamics of a vehicle. Fig. 1 shows the lateral vehicle dynamics on the global coordinate. We treat the lateral control system using the vision processing system, thus the lateral model in terms of lateral offset at look-ahead distance is useful [12]. The time derivative of lateral offset at the look-ahead distance is described by

$$\dot{e}_{yL} = V_x\left(\theta_{vf} + e_{\psi L}\right) - L\dot{\psi}^d. \qquad (1)$$

Since $\theta_{vf} = \beta + L\dot{\psi}/V_x$ and $\dot{e}_y = V_x\left(e_\psi - \beta\right)$, we see that

$$\begin{aligned}\dot{e}_{yL} &= V_x\beta + L\dot{\psi} + V_x e_{\psi L} - L\dot{\psi}^d \\ &= \dot{e}_y - V_x e_\psi + L\dot{\psi} + V_x e_{\psi L} - L\dot{\psi}^d.\end{aligned}$$

Here, by defining

$$e_{\psi L} = e_\psi + \eta_L,$$

where η_L denotes the difference between yaw angles at the vehicle's center of gravity (c.g.) and at the look-ahead distance, equation (1) can be rewritten as

$$\dot{e}_{yL} = \dot{e}_y + L\dot{\psi} + V_x\eta_L - L\dot{\psi}^d.$$

Then, the state-space model in terms of the state vector $\mathbf{x} = \left[e_{yL} \quad \dot{e}_y \quad e_\psi \quad \dot{\psi}\right]^T$, the control input $\mathbf{u} = \delta$ and output $\mathbf{y} = \left[e_{yL} \quad e_\psi \quad \dot{\psi}\right]^T$ is obtained as :

$$\begin{aligned}\dot{\mathbf{x}} &= A\mathbf{x} + B_2\mathbf{u} + B_q\mathbf{q} \\ \mathbf{y} &= C\mathbf{x},\end{aligned} \qquad (2)$$

where

$$a_{22} = -\frac{2C_{\alpha f} + 2C_{\alpha r}}{mV_x},\quad a_{23} = -a_{22}V_x,\quad a_{24} = -1 - \frac{2C_{\alpha f}l_f - 2C_{\alpha r}l_r}{mV_x^2},$$

$$a'_{24} = (a_{24} - 1)V_x,\quad a_{42} = -\frac{2C_{\alpha f}l_f - 2C_{\alpha r}l_r}{I_z},\quad a'_{42} = \frac{a_{42}}{V_x},\quad a_{43} = -a_{42},$$

$$a_{44} = -\frac{2C_{\alpha f}l_f^2 + 2C_{\alpha r}l_r^2}{I_zV_x},\quad b_{21} = \frac{2C_{\alpha f}}{mV_x},\quad b'_{21} = b_{21}V_x,\quad b_{41} = \frac{2C_{\alpha f}l_f}{I_z},$$

$$\mathbf{q} = \begin{bmatrix} \dot{\psi}^d \\ \eta_L \end{bmatrix},\quad A = \begin{bmatrix} 0 & 1 & 0 & -L \\ 0 & a_{22} & a_{23} & a'_{24} \\ 0 & 0 & 0 & -1 \\ 0 & a'_{42} & a_{43} & a_{44} \end{bmatrix},\quad B_2 = \begin{bmatrix} 0 \\ b'_{21} \\ 0 \\ b_{41} \end{bmatrix},$$

$$B_q = \begin{bmatrix} L & V_x \\ V_x & 0 \\ 1 & 0 \\ 0 & 0 \end{bmatrix},\quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

The discretization of (2) using the zero-order hold (ZOH) equivalence at sampling rate $1/T_c$ leads to the discrete-time matrices $(\Phi, \Gamma_2, \Gamma_q, C)$ from (A, B_2, B_q, C) such that

$$\mathbf{x}(k+1) = \Phi\mathbf{x}(k) + \Gamma_2\mathbf{u}(k) + \Gamma_q\mathbf{q}(k)$$
$$\mathbf{y}(k) = C\mathbf{x}(k),$$

where

$$\Phi = e^{AT_c},\ \Gamma_2 = \int_0^{T_c} e^{A(T_c - v)}B_2 dv,\ \Gamma_q = \int_0^{T_c} e^{A(T_c - v)}B_q dv.$$

3. MODEL PREDICTIVE CONTROLLER FOR LANE KEEPING SYSTEM

In this section, we design the MPC for lane keeping system based on the prediction equation. The prediction equation is developed based on the estimated signals from the multi-rate Kalman filter.

3.1. Design of multi-rate Kalman filter

The output y can be measured or available from the vision processing system and IMU. The update periods of states, however, are different according to sensors configurations : The vision processing system provides the information of road lane such as lateral offset, heading angle, curvature and curvature derivative with respect to the vehicle's c.g. at a slow sampling rate of $1/T_{cam}$. The IMU provides the values of steering wheel angle, ratio of steering wheel angle, and yaw rate at the same sampling rate as that of car ECU, $1/T_c$. For the simplicity of presentation, we assume that T_{cam} is an integer-multiple of T_c and all measurements are synchronized, that is, $T_{cam} = R_mT_c,\ R_m \geq 1,\ R_m \in \mathbb{N}$. We can, thus, represent a time instant

$$t = (k + i/R_m)T_{cam},\ k = 0,1,\ldots,\ \text{and}\ i = 0,1,\ldots,R_m - 1,$$

where k and i indicate the vision processing update and the control update instance, respectively. To estimate the all states in (2) at the rate of $1/T_c$, a multi-rate Kalman filter is designed for the partitioned dynamics $\mathbf{x} = [\mathbf{x}_v\ \ \mathbf{x}_m]^T$ comprising the state $\mathbf{x}_v = [e_{yL}\ \ \dot{e}_y\ \ e_\psi]^T$ having slow measurement sampling rates and the state $\mathbf{x}_m = [\dot{\psi}]$ having fast measurement sampling rates [12].

The slow dynamics related with the data from vision processor can be arranged as :

$$\dot{\mathbf{x}}_v = A_v\mathbf{x}_v + B_v\mathbf{u} + B_\psi\mathbf{x}_m + B_q\mathbf{q}$$
$$\mathbf{y}_v = C_v\mathbf{x}_v, \tag{3}$$

where

$$A_v = \begin{bmatrix} 0 & 1 & 0 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & 0 \end{bmatrix},\ B_v = \begin{bmatrix} 0 \\ b'_{21} \\ 0 \end{bmatrix},\ B_\psi = \begin{bmatrix} -L \\ a'_{24} \\ -1 \end{bmatrix},$$

$$B_q = \begin{bmatrix} L & V_x \\ V_x & 0 \\ 1 & 0 \end{bmatrix},\ C_v = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix},\ \mathbf{q} = \begin{bmatrix} \dot{\psi}^d \\ \eta_L \end{bmatrix}.$$

The discretization of (3) using the ZOH equivalence at sampling rate $1/T_c$ leads to the discrete-time matrices ($\Phi_v, \Gamma_v, \Gamma_\psi, \Gamma_q$) from (A_v, B_v, B_ψ, B_q). Then the estimated slow state vector $\hat{\mathbf{x}}_v$ is obtained by designing the following Kalman filter :

$$\bar{\mathbf{x}}_v(k, i+1) = \Phi_v\hat{\mathbf{x}}_v(k,i) + \Gamma_v\mathbf{u}(k,i) + \Gamma_\psi\hat{\mathbf{x}}_m(k,i) + \Gamma_q\mathbf{q}(k,i) \tag{4}$$
$$\hat{\mathbf{x}}_v(k,i) = \bar{\mathbf{x}}_v(k,i) + L_v(\mathbf{y}_v(k,0) - C_v\bar{\mathbf{x}}_v(k,0)),$$

where L_v is state estimator gain to be chosen off-line such that the mean square state estimation error is the smallest possible. Through this current estimator, the predicted state vector $\bar{\mathbf{x}}_v$ is corrected as $\hat{\mathbf{x}}_v$ based on the measurement data $\mathbf{y}_v(k,0)$ [13].

The fast dynamics related with the data from IMU can be described as:

$$\dot{\mathbf{x}}_m = A_m\mathbf{x}_m + B_m\mathbf{u} + B_{xv}\mathbf{x}_v$$
$$\mathbf{y}_m = C_m\mathbf{x}_m, \tag{5}$$

where

$$A_m = [a_{44}],\ B_m = [b_{41}],\ B_{xv} = [0\ \ a'_{42}\ \ a_{43}],\ C_m = [1].$$

The discretization of (5) using the ZOH method at sampling rate $1/T_c$ leads to the discrete-time matrices ($\Phi_m,\Gamma_m,\Gamma_{xv}$) from ($A_m,B_m,B_{xv}$). Then the estimated state vector $\hat{\mathbf{x}}_m$ is obtained by designing the following Kalman filter :

$$\begin{aligned}\bar{\mathbf{x}}_m(k,i+1)&=\Phi_m\hat{\mathbf{x}}_m(k,i)+\Gamma_m\mathbf{u}(k,i)+\Gamma_{xv}\hat{\mathbf{x}}_v(k,i)\\ \hat{\mathbf{x}}_m(k,i)&=\bar{\mathbf{x}}_m(k,i)+L_m\left(\mathbf{y}_m(k,i)-C_m\bar{\mathbf{x}}_m(k,i)\right),\end{aligned}\qquad(6)$$

where L_m is state estimator gain. Due to the designed multi-rate Kalman filter, all of states in (6) can be estimated at the same rate as ECU rate. Even though we only treat the case when R_m is a fixed integer, the Kalman filter can be generalized straightforwardly to case when R_m is a randomly varied integer [14].

3.2. Design of model predictive controller

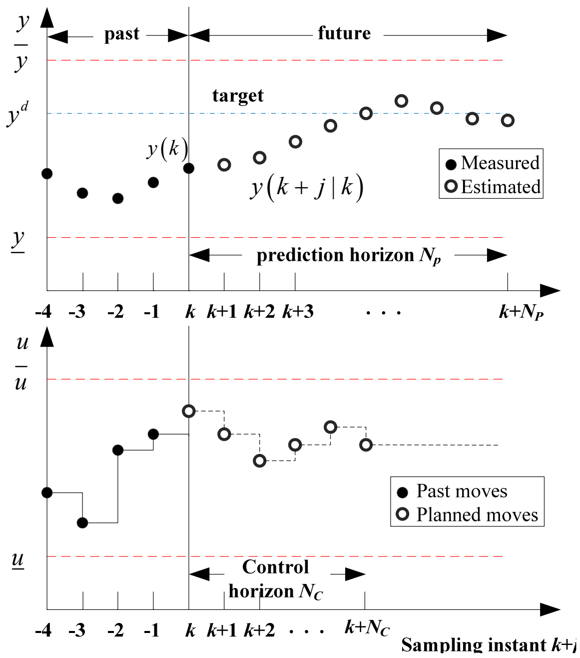


Fig. 2 Controller state at the k-th sampling instant

For the LKS, the control objective is following the desired lateral offset trajectory with the fulfillment under various constraints reflecting the vehicle physical limits and industrial control specifications. The MPC is an effective method to treat the tracking system by incorporating the constraints into the controller formulation. The MPC computes a set of optimal inputs that will drive the plant to the desired trajectory without violating constraints [7] as shown in Fig. 2. The input constraints for the LKS such as steer angle and steer angle ratio are from the attributes of steering electric power steering. The constrained optimization problem can be solved by online quadratic programming (QP) at each sampling time using the current states and previous input value [15].

Let us define lifting matrices $\tilde{\mathbf{u}}(k)$, $\Delta\tilde{\mathbf{u}}(k)$, $\tilde{\mathbf{x}}(k)$, $\tilde{\mathbf{y}}(k)$ for the input $\mathbf{u}(k)$, incremental input $\Delta\mathbf{u}(k)=\mathbf{u}(k)-\mathbf{u}(k-1)$, state $\mathbf{x}(k)$, and output prediction $\mathbf{y}(k)$ such as

$$\tilde{\mathbf{u}}(k)=\begin{bmatrix}\mathbf{u}(k)\\ \vdots\\ \mathbf{u}(k+N_c-1)\end{bmatrix},\Delta\tilde{\mathbf{u}}(k)=\begin{bmatrix}\Delta\mathbf{u}(k)\\ \vdots\\ \Delta\mathbf{u}(k+N_c-1)\end{bmatrix},$$
$$\tilde{\mathbf{x}}(k)=\begin{bmatrix}\mathbf{x}(k)\\ \vdots\\ \mathbf{x}(k+N_p-1)\end{bmatrix},\tilde{\mathbf{y}}(k)=\begin{bmatrix}\mathbf{y}(k)\\ \vdots\\ \mathbf{y}(k+N_p-1)\end{bmatrix}.$$

Then, the lifted input and output matrices can be rewritten as

$$\begin{aligned}\Delta\tilde{\mathbf{u}}(k)&=\tilde{\mathbf{u}}(k)-\tilde{\mathbf{u}}(k-1)\\ \tilde{\mathbf{y}}(k)&=\tilde{C}\tilde{\mathbf{x}}(k),\end{aligned}$$

where

$$\tilde{C}=diag(\underbrace{C,\cdots,C}_{N_P}).$$

The variables $\mathbf{r}(k+i)$ denotes reference trajectory at time $k+i$ based on the information available at time k. Then, the solution of MPC problem, i.e. $\Delta\tilde{\mathbf{u}}(k)$, at time k is obtained by solving the following dynamic objective function J:

$$J=\min_{\Delta\tilde{\mathbf{u}}}\sum_{i=1}^{N_p}Q\left\{\mathbf{y}(k+i)-\mathbf{r}(k+i)\right\}^2+\sum_{i=0}^{N_c-1}R\Delta\mathbf{u}(k+i)^2,\qquad(7)$$

subject to

$$\begin{aligned}\tilde{\mathbf{u}}_{\min}&\le\tilde{\mathbf{u}}(k)\le\tilde{\mathbf{u}}_{\max}\\ \Delta\tilde{\mathbf{u}}_{\min}&\le\Delta\tilde{\mathbf{u}}(k)\le\Delta\tilde{\mathbf{u}}_{\max}\\ \tilde{\mathbf{y}}_{\min}&\le\tilde{\mathbf{y}}(k)\le\tilde{\mathbf{y}}_{\max}.\end{aligned}$$

The objective function involves two contributions. The first term in (7) represents the penalty on trajectory tracking error and the second term in (7) penalizes the steering effort. Usually the output prediction horizon N_P is larger than the control horizon N_C.

From lateral dynamics model (2), the output prediction is described by

$$\begin{aligned}\tilde{\mathbf{y}}(k)&=\tilde{C}\tilde{\mathbf{x}}(k)\\ &=\Psi\mathbf{x}(k)+\Theta\Delta\tilde{\mathbf{u}}(k)+\Upsilon\mathbf{u}(k-1),\end{aligned}\qquad(8)$$

where

$$\Psi=\tilde{C}\begin{bmatrix} I \\ \Phi \\ \vdots \\ \Phi^{N_c-1} \\ \vdots \\ \Phi^{N_p-1}\end{bmatrix},\ \Theta=\tilde{C}\begin{bmatrix} 0 & 0 & 0 \\ \Gamma_2 & 0 & 0 \\ \vdots & \ddots & 0 \\ \sum_{i=0}^{N_c-1}\Phi^i\Gamma_2 & \cdots & \Gamma_2 \\ \vdots & & \vdots \\ \sum_{i=0}^{N_p-2}\Phi^i\Gamma_2 & \cdots & \sum_{i=0}^{N_p-N_c-1}\Phi^i\Gamma_2 \end{bmatrix},\ \Upsilon=\tilde{C}\begin{bmatrix} 0 \\ \Gamma_2 \\ \vdots \\ \sum_{i=0}^{N_c-1}\Phi^i\Gamma_2 \\ \vdots \\ \sum_{i=0}^{N_p-2}\Phi^i\Gamma_2\end{bmatrix}.$$

Then the object function J in (7) can be rewritten as

$$\begin{aligned} J &= \left(\tilde{\mathbf{y}}(k)-\tilde{\mathbf{r}}(k)\right)^T Q\left(\tilde{\mathbf{y}}(k)-\tilde{\mathbf{r}}(k)\right)+\Delta\tilde{\mathbf{u}}^T(k)R\Delta\tilde{\mathbf{u}}(k) \\ &= \left(\Theta\Delta\tilde{\mathbf{u}}(k)-\tilde{\mathbf{c}}(k)\right)^T Q\left(\Theta\Delta\tilde{\mathbf{u}}(k)-\tilde{\mathbf{c}}(k)\right)+\Delta\tilde{\mathbf{u}}^T(k)R\Delta\tilde{\mathbf{u}}(k) \\ &\equiv \frac{1}{2}\Delta\tilde{\mathbf{u}}^T(k)H\Delta\tilde{\mathbf{u}}(k)+\Delta\tilde{\mathbf{u}}^T(k)f+f_0, \end{aligned} \tag{9}$$

where

$$\tilde{\mathbf{c}}(k)=\tilde{\mathbf{r}}(k)-\Psi\mathbf{x}(k)-\Upsilon\mathbf{u}(k-1)$$
$$H=2\left(\Theta^TQ\Theta+R\right),\ f=-2\Theta^TQ\tilde{\mathbf{c}}(k),\ f_0=\tilde{\mathbf{c}}^T(k)Q\tilde{\mathbf{c}}(k).$$

The constraints of the lifted output, steer angle and rate can be put in the form of

$$\begin{aligned} &\mathbf{y}_{\min}\le\mathbf{y}(k)\le\mathbf{y}_{\max} \\ &\mathbf{u}_{\min}\le\mathbf{u}(k)\le\mathbf{u}_{\max} \\ &\Delta\mathbf{u}_{\min}\le\Delta\mathbf{u}(k)\le\Delta\mathbf{u}_{\max}. \end{aligned}$$

The constraint of the lifted output is described by $\tilde{\mathbf{y}}(k)\le\mathbf{y}_{\max}$, $-\tilde{\mathbf{y}}(k)\le-\mathbf{y}_{\min}$, then the constraint is rewritten as

$$\begin{bmatrix} I_{n_y\times N_P} \\ -I_{n_y\times N_P}\end{bmatrix}\tilde{\mathbf{y}}\le\begin{bmatrix}\tilde{\mathbf{y}}_{\max} \\ -\tilde{\mathbf{y}}_{\min}\end{bmatrix}.$$

Likewise, the constraints for the horizon from the control specifications and the physical limits are given by

$$\begin{aligned} &G_y\tilde{\mathbf{y}}(k)\le g_1 \\ &G_u\tilde{\mathbf{u}}(k)\le g_2 \\ &G_{\Delta\mathbf{u}}\Delta\tilde{\mathbf{u}}(k)\le g_3, \end{aligned}$$

where

$$G_y=\begin{bmatrix} I_{n_y\times N_P} \\ -I_{n_y\times N_P}\end{bmatrix},\ G_u=\begin{bmatrix} I_{n_u\times N_C} \\ -I_{n_u\times N_C}\end{bmatrix},\ G_{\Delta u}=\begin{bmatrix} I_{n_u\times N_C} \\ -I_{n_u\times N_C}\end{bmatrix},$$
$$g_1=\begin{bmatrix}\tilde{\mathbf{y}}_{\max} \\ -\tilde{\mathbf{y}}_{\min}\end{bmatrix},\ g_2=\begin{bmatrix}\tilde{\mathbf{u}}_{\max} \\ -\tilde{\mathbf{u}}_{\min}\end{bmatrix},\ g_1=\begin{bmatrix}\Delta\tilde{\mathbf{u}}_{\max} \\ -\Delta\tilde{\mathbf{u}}_{\min}\end{bmatrix}.$$

We can find Ξ that satisfies this equality $\Xi C\mathbf{x}(k)=\Phi\mathbf{x}(k)$. Then, from the output prediction (8), the constraints for the output are obtained

$$\begin{aligned} &G_y\tilde{\mathbf{y}}(k)=G_y\left(\Xi\mathbf{y}(k)+\Theta\Delta\tilde{\mathbf{u}}(k)+\Upsilon\mathbf{u}(k-1)\right)\le g_1 \\ &\Leftrightarrow G_y\Theta\Delta\tilde{\mathbf{u}}(k)\le g_1-G_y\Xi\mathbf{y}(k)-G_y\Upsilon\mathbf{u}(k-1), \end{aligned} \tag{10}$$

where $\Xi\mathbf{y}(k)=\Phi\mathbf{x}(k)$. The constraints for the steer angle and rate are obtained

$$\begin{aligned} &\underbrace{G_u\left(I_{N_C}-\begin{bmatrix} 0 & 0 \\ I_{(N_C-1)} & 0\end{bmatrix}\right)^{-1}}_{F_d}\Delta\tilde{\mathbf{u}}(k)+G_u\begin{bmatrix}\mathbf{u}(k-1) \\ \vdots \\ \mathbf{u}(k-1)\end{bmatrix} \\ &\qquad =F_d\Delta\tilde{\mathbf{u}}(k)+F_o\mathbf{u}(k-1)\le g_2 \\ &\Leftrightarrow\quad F_d\Delta\tilde{\mathbf{u}}(k)\le g_2{}'=g_2-F_o\mathbf{u}(k-1), \end{aligned} \tag{11}$$

where

$$F_d:=G_u\left(I_{N_C}-\begin{bmatrix} 0 & 0 \\ I_{(N_C-1)} & 0\end{bmatrix}\right)^{-1},\ F_o:=G_u\underbrace{\begin{bmatrix}1 & \cdots & 1\end{bmatrix}^T}_{N_C}$$

and

$$G_{\Delta u}\Delta\tilde{\mathbf{u}}(k)\le g_3. \tag{12}$$

Then combined constraints from (10), (11), (12) are rewritten as

$$\begin{aligned} G\Delta\tilde{\mathbf{u}}(k)&=\begin{bmatrix} G_\eta\Theta \\ F_d \\ G_{\Delta u}\end{bmatrix}\Delta\tilde{\mathbf{u}}(k) \\ &\le b(k)=\begin{bmatrix} g_1 \\ g_2 \\ g_3\end{bmatrix}+\begin{bmatrix} -G_\eta\Xi & -G_\eta\Upsilon \\ 0 & -F_o \\ 0 & 0\end{bmatrix}\begin{bmatrix}\mathbf{y}(k) \\ \mathbf{u}(k-1)\end{bmatrix}. \end{aligned} \tag{13}$$

The optimization problem (9) can be treated as a QP problem of minimizing the cost function. The vector of variations of control inputs

$$\left[\Delta\mathbf{u}^*(k),\cdots,\Delta\mathbf{u}^*(k+N_C-1)\right] \tag{14}$$

is predicted at each sample time k by solving (7). The superscript * denotes the optimized value. The resulting state feedback control law at k is given by

$$\mathbf{u}(k)=\mathbf{u}(k-1)+\Delta\mathbf{u}^*(k),$$

then the vector (14) is recalculated at the next computation cycle based on the current measured state values.

Fig. 3 shows the structure of the LKS with the MPC and multi-rate Kalman filter. The lateral offset and heading angle from the center line are measured by using the camera module, and the yaw rate are measured by

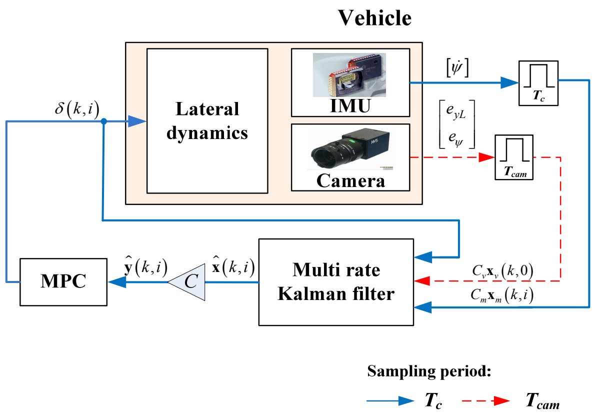


Fig. 3 Structure of the LKS with MPC and multi-rate Kalman filter

using the yaw rate sensor. We assume that the path is predefined and the controller is designed such that the vehicle should follow the path. The LKS system is implemented with the multi-rate structure, i.e., the sampling period of camera module, Tcam, is generally 6~8 times slower than that of the car ECU and inertia sensors. We thus need to design a multi-rate controller for the lateral dynamics to produce the control input at a fast rate of $1/T_c$ using the lane detection at a slow rate of $1/T_{cam}$. The steering system has constraints on the steer angle and rate. The information of lateral offset with the slow period may cause the control input to violate the constraints. The MPC solves the QP problem by computing the sequence of the control input at each T_c with the optimization the future behavior of the vehicle [7]. Thus applying MPC and multi-rate Kalman filter produces the fast sampled control input.

4. SIMULATION RESULTS

Performance of the proposed control method was validated via simulations implemented in MATLAB /Simulink and CarSim. We assume that the longitudinal speed is a constant of 30 [m/s]. The autonomous vehicle keeps tracking the curved lane with the minimum radius of 250[m].

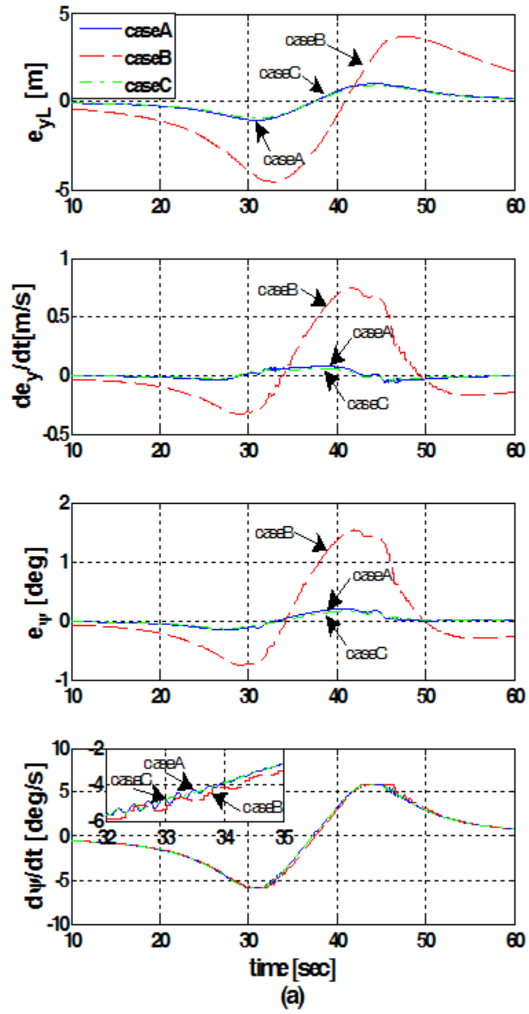
The constraints on output, input and input rate are following:

$$\begin{aligned}
-0.9454[\mathrm{deg}] &\le \mathbf{u} \le 0.9454[\mathrm{deg}] \\
-0.57296[\mathrm{deg}/s] &\le \Delta\mathbf{u} \le 0.57296[\mathrm{deg}/s] \\
-5[m] &\le y_1 \le 5[m] \\
-2[\mathrm{deg}] &\le y_2 \le 2[\mathrm{deg}] \\
-15[\mathrm{deg}/s] &\le y_3 \le 15[\mathrm{deg}/s].
\end{aligned} \tag{15}$$

For comparison, we performed simulations for three different sampling periods. Sampling periods and horizons used for the three cases are listed in Table 1. In case A, the sampling periods of the camera module is the same as that of the steering controller. It represents the case that the vehicle is equipped with the high performance vision system. In case B, we reconstruct the real system, i.e., the sampling periods of the camera is almost seven times to that of ECE sampling period. Thus control output is generated at the instance when the vision data is updated. For the comparison with the case A, we keep the other factors as the case A. In case C, we apply the proposed multi-rate Kalman filter and keep the other factors as the case B. The performance of the proposed steering control scheme is shown to be effective in improving the reference tracking performance of the multi-rate LKS.

Table 1 Simulation scenarios

Case	T_{cam}[ms]	T_c[ms]	N_p	N_c
A	10	10	10	8
B	70	70	10	8
C	70	10	10	8



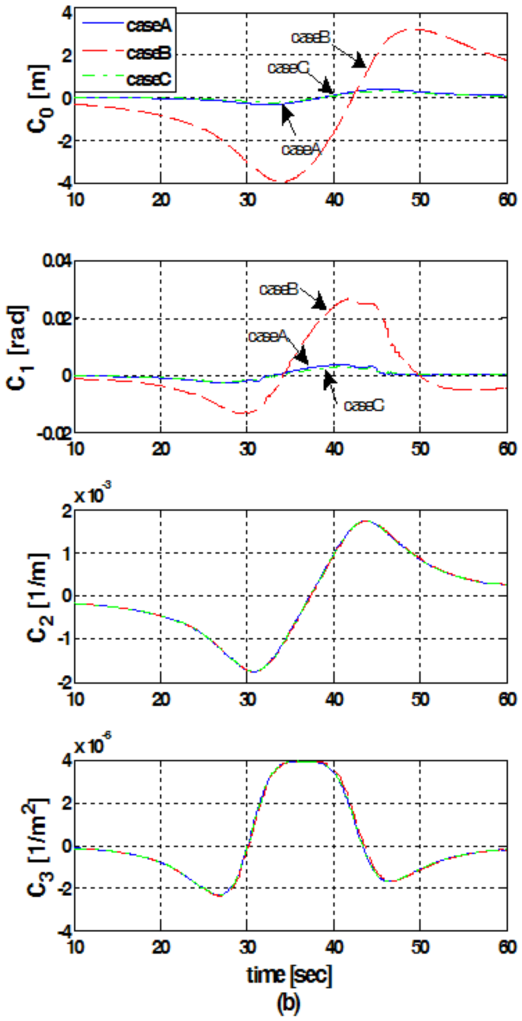


Fig. 4 Simulation results : (a) state, (b) camera data (blue-solid : case A, red-dashed : case B, green-dashed dot : case C)

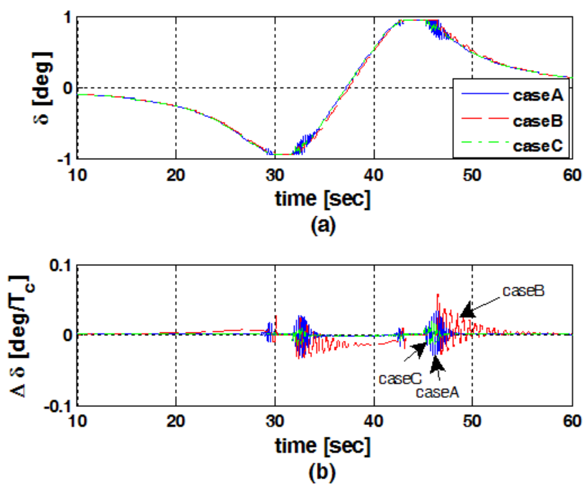


Fig. 5 (a) Steer angle, (b) rate of steer angle (blue-solid : case A, red-dashed : case B, green-dashed dot : case C)

Fig. 4(a) shows the simulation results of each state (lateral offset at look-ahead distance, time derivative of lateral offset at c.g., yaw angle error, yaw rate) and (b) shows camera data (C_0: lateral offset at c.g., C_1: heading angle, C_2: curvature, C_3: curvature derivative) of the case A, case B and case C. And Fig. 5(a) shows the steer angle that is control u and (b) shows the input variation correspond to Fig. 4. Lateral offset at look-ahead distance and heading angle are related to the differences between the ego vehicle and the road. Curvature and curvature derivative are absolute data of the road so that it does not change.

The steer angle and yaw rate are saturated due to the constraint on the steer angle. In case A, responses show good behavior because the vehicle is equipped with the high performance and high cost vision system. In case B, response has the worst performance among the three cases as the maximum lateral offset at look-ahead distance is 4.5m because the control sampling period is 70ms. In case C, though the camera sampling period is 70ms, all of state are updated from the multi-rate estimator at Tc, and it shows good performance similar to the case A. Through this results, we demonstrate that the LKS applied by MPC with the multi-rate Kalman filter improves driving performance with a low cost vision system.

4. CONCLUSION

A multi-rate steering control scheme using model predictive control was developed for autonomous vehicles. The multi-rate Kalman filter was developed to produce the control input at a rate of the car ECU despite using the vision module having slow update period. The production of control input was solvable by computing the QP problem considering the tracking performance and constraints on steering system. Simulation results showed that the lane tracking is fulfilled with a stable vehicle motion while the information from the vision system is available at a slow sampling period.

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