ISSN 1975-8359(Print) / ISSN 2287-4364(Online)
The Transactions of the Korean Institute of Electrical Engineers Vol. 67, No. 2, pp. 308~313, 2018
http://doi.org/10.5370/KIEE.2018.67.2.308

다중모바일로봇의 리더추종을 위한 샘플데이타 모델예측제어

Sampled-Data MPC for Leader-Following of Multi-Mobile Robot System

한 승 용* · 이 상 문†
(Seungyong Han · Sangmoon Lee)

Abstract - In this paper, we propose a sampled-data model predictive tracking control deign for leader-following control of multi-mobile robot system. The error dynamics of leader-following robots is modeled as a Linear Parameter Varying (LPV) model. Also, the Lyapunov function is presented to guarantee stability of the networked control system. Based on the stabilization condition using a quadratic Lyapunov function approach, model predictive sampled-data controller is designed. Finally, the leader-following control of multi mobile robots is simulated to show effectiveness of the proposed method.

Key Words : Multi-mobile robot system, Sampled-data, Leader-following control, MPC

1. Introduction

Recently, multi-mobile robot systems are widely used for military, surveillance, and transportation [1], [2]. When multiple robots move toward a target while maintaining a certain distance or angle, this is called formation [3]. In the formation control techniques, the leader-following method has been adopted by many researchers [4], [5], [6]. In this method, the leader tracks a predefined path and the follower maintains a desired geometric configuration with the leader. When multiple robots tasks, the inception of distributed robotics is important issues so that communication system has been extensively studied.

The communication network has a number of benefits simple installation and maintenance, and high reliability, increased flexibility and safety. Therefore, many of researchers are focused on this topic [7], [8].

In networked control system, the input control is delayed according to network-induced delays. The network-induced delays usually consist of two kinds of delays: the communication delays between the controller and the following mobile robots and the communication delays between the controller, the actuator and sampler. The delay may cause instability and performance degradation so that the design of control scheme should be considered with aspects to performances of whole systems [9].

In this paper, we propose a sampled-data model predictive control for leader-following multi-mobile robots in network system. To derive the condition, the LPV model [10] is considered in continuous time which reduces the difference between the dynamics of the nominal closed-loop system and the actual evolution of the state. It is explicitly assumed that the LPV model is updated only at the sampling instants and that the control signal is kept constant between two consecutive sampled by means of a zero order holder, while the plant and the parameters evolve continuously in time. In the case of periodic and aperiodic sampling time, the robustness should be guaranteed so that a quadratic Lyapunov function is considered with new looped-functionals. To deal with the single integral term in the derivative of the Lyapunov function, a generalized free-weighting-matrix (GFWM) [12] gives a less conservatism. Finally, we demonstrate the effectiveness of the proposed approach via numerical simulation.

The main contributions of this paper are summarized as follows:

(1) In the modelling aspects, we attempt to consider the modelling of multi-mobile robots in continuous time which is more accurate than the discrete time. Moreover, The MPC technique is not only adequate for the Leader-Follower model represented by error dynamics, but also consider the input saturation constraint.

(2) In the sampled-data LPV systems, based on constructing new looped-functionals and using a GFWM

† Corresponding Author : School of Electronic Engineering, Kyungpook National University, Republic of Korea.
E-mail: moony@knu.ac.kr
* School of Electronic Engineering, Kyungpook National University, Republic of Korea.
Received : December 10, 2017; Accepted : January 30, 2018

integral inequality, the proposed sampled data MPC design method for LPV systems can get a larger sampling interval upper bound than the existing one [13].

Notations: Throughout this paper, $\mathbb{R}^n$ denotes the n dimensional Euclidean space, and $\mathbb{R}^{m\times n}$ is the set of all $n\times m$ real matrices, For symmetric matrices A and B, the notation $A > B$(respectively, $A \geq B$) means that the matrix $A-B$ is positive definite (respectively, non- negative). diag{...} denotes the block diagonal matrix. * denotes the symmetric part. I denotes identity matrix with appropriate dimensions. $Sym(X)$ denotes $X+X^T$.

2. Problem formulation

Consider a multi robot system composed of a leader mobile robot and $i=1,...n$ followers. The mobile robots in two dimensions are shown in Fig. 1. The dynamics of each follower can be represented as

$$\begin{aligned}\dot{x}_i &= v_i\cos(\theta_i),\\ \dot{y}_i &= v_i\sin(\theta_i),\\ \dot{\theta}_i &= w_i\end{aligned} \tag{1}$$

which $v_i(\frac{m}{\sec})$ is linear velocity, and $w_i(\frac{rad}{\sec})$ is angular velocity. The leader labeled as $i=r$ has the same dynamics of the followers. To set up the problem, error coordinates between global and local coordination is considered by using the dynamics (1),

$$\begin{bmatrix} x_{e,r,i}\\ y_{e,r,i}\\ \theta_{e,r,i}\end{bmatrix} = \begin{bmatrix}\cos(\theta_i(t)) & \sin(\theta_i(t)) & 0\\ -\sin(\theta_i(t)) & \cos(\theta_i(t)) & 0\\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}x_r(t)-x_i(t)\\ y_r(t)-y_i(t)\\ \theta_r(t)-\theta_i(t)\end{bmatrix}. \tag{2}$$

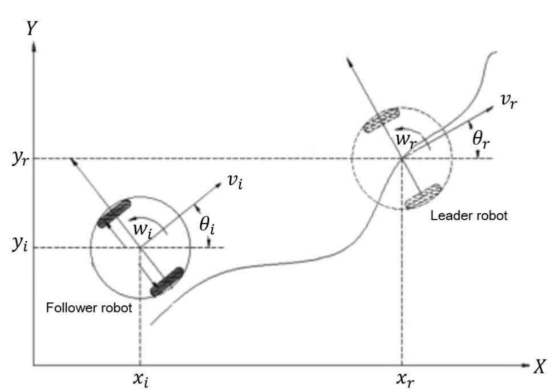

Fig. 1 Trajectory tracking error of a mobile robot in a global coordinate frame

그림 1 기준 좌표계에서 이동로봇의 궤적 추적 에러

By differentiating (2) and substituting (1) into the result, the error dynamics is obtained as

$$\begin{aligned}\dot{x}_{e,r,i}(t) &= w_i(t)y_{e,r,i}(t)+v_r\cos(\theta_{e,r,i}(t))-v_i(t),\\ \dot{y}_{e,r,i}(t) &= -w_i(t)x_{e,r,i}(t)+v_r\sin(\theta_{e,r,i}(t)),\\ \dot{\theta}_{e,r,i}(t) &= w_r-w_i(t).\end{aligned} \tag{3}$$

Further on linearizing (3) around operating point $(\bar{x}_{e,r,i}=0, \bar{y}_{e,r,i}=0, \bar{\theta}_{e,r,i}=0, \bar{v}_i=\hat{v}, \bar{w}_i=\hat{w})$ results in the following linear model

$$\dot{X}_{r,i}(t) = A(t)X_{r,i}(t)+BU_{r,i}(t) \tag{4}$$

where $X_{r,i}=[x_{e,r,i}-\bar{x}_{e,r,i}, y_{e,r,i}-\bar{y}_{e,r,i}, \theta_{e,r,i}-\bar{\theta}_{e,r,i}]$, and $U_{r,i}=[v_i-\hat{v}, w_i-\hat{w}]$. The system matrices A and B are

$$A(t) = \begin{bmatrix}0 & \hat{w}(t) & 0\\ -\hat{w}(t) & 0 & v_r(t)\\ 0 & 0 & 0\end{bmatrix},\ B=\begin{bmatrix}-1 & 0\\ 0 & 0\\ 0 & -1\end{bmatrix}. \tag{5}$$

To consider the system's less uncertainty, the range of $\hat{w}(t)$ has $\hat{w}\in[w_r(t)-\tilde{w}\, w_r(t)+\tilde{w}]$, then the all solutions of (4) can be solved between A_1 and A_2

$$A_1(t) = \begin{bmatrix}0 & w_r(t)-\tilde{w} & 0\\ -(w_r(t)-\tilde{w}) & 0 & v_r(t)\\ 0 & 0 & 0\end{bmatrix},$$

$$A_2(t) = \begin{bmatrix}0 & w_r(t)+\tilde{w} & 0\\ -(w_r(t)+\tilde{w}) & 0 & v_r(t)\\ 0 & 0 & 0\end{bmatrix}$$

which A_1 is the minimum of the $\hat{w}$, and A_2 is the maximum of the $\hat{w}$.

The network-induced input delay is considered, so the control input is defined

$$U_{r,i}(t_{k,r,i}) = K_{r,i}X_{r,i}(t_{k,r,i}) \tag{6}$$

where $K_{r,i}$ is the control gain matrix for $t\in[t_{k,r,i}\ t_{k+1,r,i})$. Without loss of generality, it is assumed that the sampled time interval is bounded by

$$h_{r,i}(t) \leq h_{Mr,i} \tag{7}$$

where $h_{r,i}(t)=t_{k+1,r,i}-t_{k,r,i}$ and $h_{Mr,i}$ is the maximum sampled delay. Using sampled signals, the LPV systems of mobile robot (4) is reformulated as delayed LPV model,

$$\dot{X}_{r,i}(t) = A_s(t)X_{r,i}(t) + BU_{r,i}(t_{k,r,i}),\ s=1,2. \tag{8}$$

To maintain the constant distance between the leader and followers,

$$X_{r,i}(t_{k,r,i}) = [x_{e,r,i}(t_{k,r,i}) - l_{x,i},\ y_{e,r,i}(t_{k,r,i}) - l_{y,i},\theta_{e,r,i}(t_{k,r,i}) - l_{\theta,i}] \tag{9}$$

where $l_{x,i}, l_{y,i}, l_{\theta,i}$ is the safety distance between the leader and ith robot in each coordinate.

Lemma 1. [11] For any constant matrices of appropriate dimensions Θ_1, Θ_2, Ψ, and a scalar $\tau(t) \in [0, \tau_M]$, the following two conditions are equivalent:

1) $\tau(t)\Theta_1 + (\tau_M - \tau(t))\Theta_2 + \Psi < 0$ (10)

2) $\tau_M\Theta_1 + \Psi < 0,$ (11)

$\tau_M\Theta_2 + \Psi < 0.$ (12)

Lemma 2. [12] Consider X is a differentiable in $[a, b] \in \mathbb{R}^n$. For matrices $R > 0$ and any matrices L and H, the following inequality holds:

$$-\int_a^b \dot{X}^T(s)R\dot{X}(s)ds \le Sym(\epsilon_0^T L\epsilon_1 + \epsilon_0^T H\epsilon_2) + (b-a)\epsilon_0^T\left(\frac{3L^TR^{-1}L + H^TR^{-1}H}{3}\right)\epsilon_0 \tag{13}$$

where ϵ_0 is any vector and $\epsilon_1 = X(b) - X(a)$,

$$\epsilon_2 = X(b) + X(a) - \frac{2}{b-a}\int_a^b X(s)ds.$$

Remark 1. From the proof of Lemma 5 [12], the generalized free-matrix inequality can be modified as

$$\int_a^b \epsilon_0^T(X^TR^{-1}X)\epsilon_0 ds = (b-a)\epsilon_0^T(X^TR^{-1}X)\epsilon_0$$

and

$$\int_a^b \lambda(s)\epsilon_0^T(H^TR^{-1}H)\lambda(s)\epsilon_0 ds = \frac{(b-a)}{3}\epsilon_0^T(H^TR^{-1}H)\epsilon_0$$

respectively.

3. Main Results

The main purpose of this paper is to design a sampled-data MPC. the essence of a MPC scheme is to optimize predictions of process behavior over a sequence of future control inputs. Therefore, the objective function to be minimized can be stated as a quadratic function of the states and control inputs:

$$J_{r,i} = \int_0^\infty X_{r,i}^T(t)QX_{r,i}(t) + U_{r,i}^T(t)RU_{r,i}(t)dt \tag{14}$$

where Q,R are weighting matrices. For the given performance index, if the following condition is satisfied

$$\dot{V}_{r,i}(t) + \| X_{r,i}(t) \|_Q^2 + \| U_{r,i}(t) \|_R^2 < 0 \tag{15}$$

then the upper bound of the performance index can be derived instead of directly minimizing performance index.

Before deriving conditions, following notations are defined.

$$d_{r,i}(t) = t - t_{k,r,i},$$
$$e_1 = [I\,0\,0\,0],\ e_2 = [0\,I\,0\,0],\ \ldots, e_4 = [0\,0\,0\,I],$$
$$F_1 = [I\ \ -I\ 0\ 0],$$
$$F_2 = [I\,I\,0\ \ -2I],$$
$$\overline{f_s} = [A_sM\ BY\ -M\ 0],\ \ s=1,2,$$
$$f_s = [A_s\ BK\ -I\ 0],$$
$$\zeta_{r,i}(t_{k,r,i}) = [X_{r,i}^T(t)\ \ X_{r,i}^T(t_{k,r,i})\ \ \dot{X}_{r,i}^T(t)\ \ \frac{1}{t-t_{k,r,i}}\int_{t_{k,r,i}}^t X_{r,i}^T(s)ds]^T.$$

Theorem 1. For a given with maximum sampling interval h_M, the continuous system (1) is asymptotically stabilizable if there exist matrices $\dot{P} > 0, \overline{P_1} > 0$, $S = \begin{bmatrix} S_1 & S_2 \\ * & S_3 \end{bmatrix} > 0, M, \overline{L},\ \overline{H}, U_{M,r,i}$ and the control input at time instant $t_{k,r,i}$ guarantees the performance index (13) with $\gamma_{r,i}$.

$$\min \gamma_{r,i} \tag{16}$$

$$\begin{bmatrix} 1 & X_{r,i}(t_{k,r,i}) \\ * & M^T + M - P_0 \end{bmatrix} \ge 0, \tag{17}$$

$$\Xi_1^s < 0,\ \text{for}\ s=1,2, \tag{18}$$

$$\Xi_2^s < 0,\ \text{for}\ s=1,2, \tag{19}$$

$$\begin{bmatrix} M^T + M - P_0 & Y \\ * & U_{M,r,i} \end{bmatrix} \ge 0 \tag{20}$$

where

$$U_{M,r,i}=\begin{bmatrix} u^{11}_{M,r,i} & 0 \\ * & u^{22}_{M,r,i} \end{bmatrix}, \begin{matrix} u^{11}_{M,r,i} \le (v_i-\hat{v})^2_{\max} \\ u^{22}_{M,r,i} \le (w_i-\hat{w})^2_{\max} \end{matrix}$$

$$\Xi^s_1=\begin{bmatrix} \Xi^s_{11} & \Xi_{12} & h_{M,r,i}\bullet \overline{L} & h_{M,r,i}\bullet \overline{H} \\ * & \Xi_{22} & 0 & 0 \\ * & * & -h_{M,r,i}\bullet \overline{S}_3 & 0 \\ * & * & * & -h_{M,r,i}\bullet \overline{S}_3 \end{bmatrix},$$

$$\Xi^s_2=\begin{bmatrix} \Xi^{2s}_{11} & \Xi_{12} \\ * & \Xi_{22} \end{bmatrix},$$

$$\Xi_{12}=diag[M,Y],$$

$$\Xi_{22}=diag[-\gamma_{r,i}Q^{-1},-\gamma_{r,i}R^{-1}],$$

with

$$\begin{aligned}\Xi_1 &= e_1^T P_0 e_3+(e_1^T P_0 e_3)^T \\ &+(e_1-e_2)^T\overline{P}_1 e_3+((e_1-e_2)^T\overline{P}_1 e_3)^T \\ &+Sym(\overline{Z}_1F_1+\overline{Z}_2F_2)-e_2^T\overline{S}_2(e_1-e_2) \\ &-(e_2^T\overline{S}_2(e_1-e_2))^T+(e_1+\alpha e_4)^T\overline{f}_i \\ &+((e_1+\alpha e_4)^T\overline{f}_i)^T, \\ \Xi_2 &= e_4^T\overline{P}_1e_1+(e_4^T\overline{P}_1e_1)^T-e_2^T\overline{S}_1e_2 \\ &-e_4^T\overline{Z}e_2-(e_4^T\overline{Z}e_2)^T, \\ \Xi_3 &= \begin{bmatrix} e_2 \\ e_3 \end{bmatrix}^T\overline{S}\begin{bmatrix} e_2 \\ e_3 \end{bmatrix}+e_1^T\overline{Z}e_2+(e_1^T\overline{Z}e_2)^T.\end{aligned}$$

In addition, the state feedback gains are given as $K_{r,i}=YM^{-1}$.

Proof. Choosing the following Lyapunov function for $t\in[t_{k,r,i},t_{k+1,r,i}]$ yields

$$V_{r,i(x_t)}=V_{1,r,i}(t)+V_{2,r,i}(t)+V_{3,r,i}(t) \tag{21}$$

where

$$V_{1,r,i}(t)=X^T_{r,i}(t)M^{-T}P_0M^{-1}X_{r,i}(t),$$

$$V_{2,r,i}(t)=\begin{bmatrix} X_{r,i}(t)-X_{r,i}(t_{k,r,i}) \\ \int_{t_{k,r,i}}^t X_{r,i}(s)ds \end{bmatrix}^T P_1\begin{bmatrix} X_{r,i}(t)-X_{r,i}(t_{k,r,i}) \\ \int_{t_{k,r,i}}^t X_{k,r,i}ds \end{bmatrix},$$

$$\begin{aligned}V_{3,r,i}(t) &= (t_{k+1,r,i}-t)(\int_{t_{k,r,i}}^t \begin{bmatrix} X_{r,i}(t_{k,r,i}) \\ \dot{X}_{r,i}(t) \end{bmatrix}^T S\begin{bmatrix} X_{r,i}(t_{k,r,i}) \\ \dot{X}_{r,i}(t) \end{bmatrix}ds) \\ &+2\int_{t_{k,r,i}}^t X^T_{r,i}(s)dsZX_{r,i}(t_{k,r,i}).\end{aligned}$$

Differentiate the Lyapunov function

$$\dot{V}_{1,r,i}(t)=2e_1^TM^{-T}P_0M^{-1}e_3, \tag{22}$$

$$\dot{V}_{2,r,i}(t)=2\begin{bmatrix} e_1-e_2 \\ d_{r,t}(t)e_4 \end{bmatrix}^T P_1\begin{bmatrix} e_3 \\ e_1 \end{bmatrix}, \tag{23}$$

$$\begin{aligned}\dot{V}_{3,r,i}(t) &= -d_{r,i}(t)e_2^TS_1e_2-2e_2^TS_2(e_1-e_2) \\ &-2d_{r,i}(t)e_4^TZe_2 \\ &+(h_{M,r,i}-d_{r,i}(t))(\begin{bmatrix} e_2 \\ e_3 \end{bmatrix}^T S\begin{bmatrix} e_2 \\ e_3 \end{bmatrix}+2e_1^TZe_2) \\ &-\int_{t_{k,ri}}^t \dot{X}^T_{r,i}(s)S_3\dot{X}_{r,i}(s)ds.\end{aligned} \tag{24}$$

From Lemma 2, the following holds

$$\begin{aligned}&-\int_{t_{k,r,i}}^t \dot{X}^T_{r,i}(s)S_3\dot{X}_{r,i}ds \\ &\le Sym(\epsilon_0^TL\epsilon_1+\epsilon_0^TH\epsilon_2)+d_{r,i}(t)\epsilon_0^T(\frac{3L^TS_3^{-1}L+H^TS_3^{-1}H}{3})\epsilon_0\end{aligned} \tag{25}$$

where L, H are auxiliary variables. Taking into account system dynamics (8),

$$\begin{aligned}&2[X^T_{r,i}(t)M^{-1}+\alpha\dot{X}^T_{r,i}(t)M^{-1}][-\dot{X}_{r,i}(t)+A_sX_{r,i}(t) \\ &+BK_{r,i}X_{r,i}(t_{k,r,i})].\end{aligned} \tag{26}$$

Summing up from (22) to (26) leads to

$$\begin{aligned}&\dot{V}_{r,i}+X^T_{r,i}(t)QX_{r,i}(t)+U^T_{r,i}(t)RU_{r,i}(t) \\ &\le \zeta_{r,i}(t_{k,r,i})\overline{\Xi}\zeta_{r,i}(t_{k,r,i})\end{aligned} \tag{27}$$

where

$$\begin{aligned}\overline{\Xi} &= \overline{\Xi}_1+d_{r,i}(t)\overline{\Xi}_2+(h_{M,r,i}-d_{r,i}(t))\overline{\Xi}_3, \\ \overline{\Xi}_1 &= e_1^TP_0e_3+(e_1^TP_0e_3)^T+(e_1-e_2)^TP_1e_3 \\ &+((e_1-e_2)^TP_1e_3)^T+Sym(Z_1F_1+Z_2F_2) \\ &-e_2^TS_2(e_1-e_2)-(e_2^TS_2(e_1-e_3))^T \\ &+(e_1+\alpha e_4)^Tf_i+((e_1+\alpha e_4)^Tf_i)^T \\ &+e_1^TQe_1+e_2^TK^T_{r,i}RK_{r,i}e_2, \\ \overline{\Xi}_2 &= e_4^TP_1e_1+(e_4^TP_1e_1)^T-e_2^TS_1e_2 \\ &-e_4^TZe_2-(e_4^TZe_2)^T \\ &+L^TS_3^{-1}L+\frac{1}{3}H^TS_3^{-1}H, \\ \overline{\Xi}_3 &= \begin{bmatrix} e_2 \\ e_3 \end{bmatrix}^T S\begin{bmatrix} e_2 \\ e_3 \end{bmatrix}+e_1^TZe_2+(e_1^TZe_2)^T.\end{aligned} \tag{28}$$

Pre-and post-multiplying with a matrix

$\gamma_{r,i}^{\frac{1}{2}} \times \{diagM, M, M, M\}$, the followings are satisfied with Lemma 1.

$$\Xi_1 + h_{M,r,i}\Xi_2 + h_{M,r,i}(\overline{L}^T \overline{S}_3^{-1} \overline{L}) + \frac{1}{3}h_{M,r,i}(\overline{H}^T \overline{S}_3^{-1} \overline{H}) < 0, \quad (29)$$

$$\Xi_1 + h_{M,r,i}\Xi_3 < 0 \quad (30)$$

where $\overline{S} = MSM, \overline{L} = MLM, \overline{H} = MHM$, and $K_{r,i} = YM^{-1}$. Using Schur complement, the equations in (18) and (19) are equivalent to those of (11) and (12). For every sampling instance, $V_{2,r,i}$ and $V_{3,r,i}$ vanish. Then, the upper bound of Lyapunov function is expressed in terms of $V_{1,r,i}$.

$$X_{r,i}^T(t_{k,r,i}) MP_0 M X_{r,i}(t_{k,r,i}) \leq \gamma_{r,i}, \quad (31)$$

where $\gamma_{r,i}$ denotes the bound of optimal performance index. The input saturation is considered similar to the method in [14]. This ends the proof. □

4. Numerical Examples

The dynamical equation (8) is considered as

$$\dot{X}_{r,1}(t) = A_s(t) X_{r,1}(t) + BU_{r,1}(t - h_{r,1}(t)). \quad (32)$$

where

$$A_1(t) = \begin{bmatrix} 0 & w_r(t) - 0.03 & 0 \\ -(w_r(t) - 0.03) & 0 & v_r \\ 0 & 0 & 0 \end{bmatrix},$$

$$A_2(t) = \begin{bmatrix} 0 & w(t) + 0.03 & 0 \\ -(w_r(t) + 0.03) & 0 & v_r(t) \\ 0 & 0 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} -1 & 0 \\ 0 & 0 \\ 0 & -1 \end{bmatrix}.$$

The model parameters are calculated with a sampling time 0.8s. The sampling time $h_{r,1}$ is less than 0.8s. Along the reference trajectory $(v_r = 0.2, w_r = 0.2)$, the input is constrained to $-0.3 \leq (v_1 - \hat{v}) \leq 0.3$ and $-0.3 \leq (w_1 - \hat{w}) \leq 0.3\,(\tilde{w} = 0.03)$. The corresponding controller gain matrix is

$$K_{r,1} = \begin{bmatrix} 0.6775 & -0.1771 & -0.0906 \\ -0.0880 & 0.3650 & 0.7873 \end{bmatrix}. \quad (33)$$

Fig 2 and 3 show the simulation results which are obtained with the above controller gain, taking $Q = I$, $R = I$, $\alpha = 0.1$.

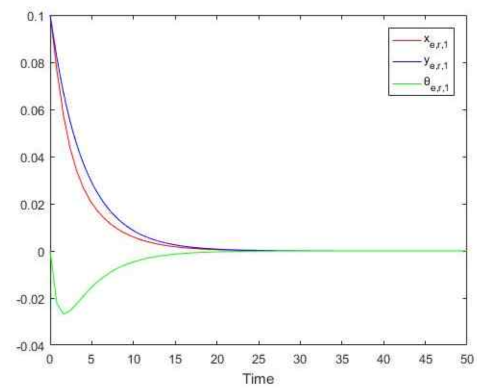

Fig. 2 The error response of the system
그림 2 시스템 에러 응답

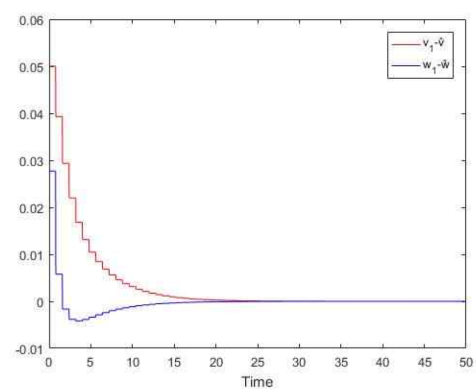

Fig. 3 The sampled-data control input with constraints
그림 3 입력제한을 고려한 샘플데이타 제어입력

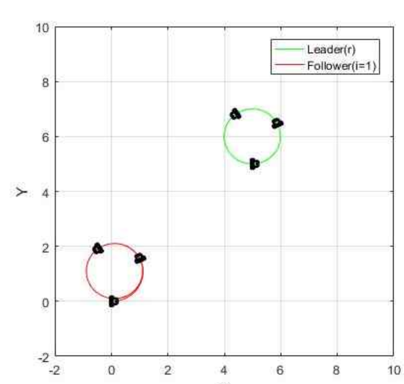

Fig. 4 The trajectory of each robot(r, $i=1$) at time $t=0$, 10 50(sec)
그림 4 리더(r)와 첫 번째($i=1$)추종 로봇의 시간 $t=0$, 10 50(초)에서의 궤적

5. Conclusions

The sampled-data MPC method for multi-mobile robot systems have been investigated by considering polytopic LPV model. Based on the quadratic Lyapunov function approach, sufficient conditions for the sampled-data MPC controller are derived by constructing new looped-functionals. The proposed method guarantees a performance and stability in much longer sampling delay than the existing paper. The effectiveness of the presented method has been verified by illustration numerical simulation.

Acknowledgement

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2016R1D1A1B03930623).

References

[1] R. M. Murray, Recent research in cooperative control of multi vehicle systems, Journal of Dynamic Systems, Measurement, and Control, vol. 129, no. 5, pp. 571-583, 2007.

[2] J. McLurkin, J. Rykowski, M. John, Q. Kaseman, and A. J. Lynch, Using multi-robot systems for engineering education: Teaching and outreach with large numbers of an advanced, low cost robot, vol. 56, no. 1, pp. 24-33, 2013.

[3] Y. Q. Chen, Z. Wang, Formation control: a review and a new consideration. In Intelligent Robots and Systems, IEEE, 2005 IEEE/RSJ International Conference, pp. 3181-3186, 2005.

[4] A. K. Das. R. Fierro, V. Kumar, J. P. Ostrowski, J. Spletzer and C. J. Taylor, A vision-based 60 formation control framework, IEEE Trans, vol. 18, no. 5, pp. 813-825, 2002.

[5] W. Zhu, Z. P. Jiang, Event-based leader-following consensus of multi-agent systems with input time delay, IEEE Trans, vol. 60, no. 5, pp. 1362-1367, 2015.

[6] G. Wen, C. P. Chen, Y. J. Liu, and Z. Liu, Neural network-based adaptive leader-following consensus control for a class of nonlinear multi agent state-delay systems, IEEE Trans, vol. 47, no. 8, pp. 1927-1934, 2017.

[7] L. Sheng, Y. J. Pan, X. Gong, Consensus formation control for a class of networked multiple mobile robot systems, Journal of Control Science and Engineering, vol. 2012, pp. 1-12, 2012.

[8] Y. Hong, G. Chen, L. Bushnell, Distributed observers design for leader-following control of 70 multi-agent networks, Automatica, vol. 44, no. 3, pp. 846-850, 2008.

[9] L. Ding, Q. L. Han, G. Guo, Network-based leader-following consensus for distributed multi-agent systems, Automatica, vol. 49, no. 7, pp. 2281-2286, 2013.

[10] W. Lucia, F. Tedesco, A networked-based receding horizon scheme for constrained LPV systems, European Journal of Control, vol. 25, pp. 69-75, 2015.

[11] D. Yue, E. Tian, Y. Zhang, and C. Peng, Delay-distribution-dependent stability and stabilization of T-S fuzzy systems with probabilistic interval delay, IEEE Trans, vol. 39, no. 2, pp. 503-516, 2009.

[12] C. K. Zhang, Y. He, L. Jiang, W. Lin, M. Wu, Delay-dependent stability analysis of neural networks with time-varying delay: A generalized free-weighting-matrix, Applied Mathematics and Computation, vol. 294, no. 1, pp. 102-120, 2017.

[13] W. Kwon, S. M. Lee, Sampled-Data Model Predictive Tracking Control for Mobile Robot, IJCAS, vol. 11, no. 4, pp. 456-459, 2017.

[14] E. Fridman and M. Dambrine, Control under quantization, saturation and delay: An LMI approach, Automatica, vol. 45, no. 10, pp. 2258-2264, 2009.

저 자 소 개

한 승 용 (Seungyong Han)

1992년 1월 15일생. 2016년 영남대학교 물리학과 졸업(이학). 현재 경북대학교 전자공학부 석사과정.

E-mail : dds8946@knu.ac.kr

이 상 문 (Sangmoon Lee)

1973년 6월 15일생. 1999년 경북대학교 전자공학과 졸업(공학). 2006년 포항공과대학교 전기전자공학부 졸업(공박). 현재 경북대학교 전자공학부 부교수.

E-mail : moony@knu.ac.kr