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Networked operation of a UAV using Gaussian process-based delay compensation and model predictive control

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***Abstract*— This study addresses an operation of unmanned aerial vehicles (UAVs) in a network environment where there is time-varying network delay. The network delay entails undesirable effects on the stability of the UAV control system due to delayed state feedback and outdated control input. Although several networked control algorithms have been proposed to deal with the network delay, most existing studies have assumed that the plant dynamics is known and simple, or the network delay is constant. These assumptions are improper to multirotor-type UAVs because of their nonlinearity and time-sensitive characteristics. To deal with these problems, we propose a networked control system using model predictive control (MPC) designed under the consideration of multirotor characteristics. We also apply a Gaussian process (GP) to learn an unknown nonlinear model, which increases the accuracy of path planning and state estimation. Flight experiments show that the proposed algorithm successfully compensates the network delay and Gaussian process learning improves the UAV's path tracking performance.**

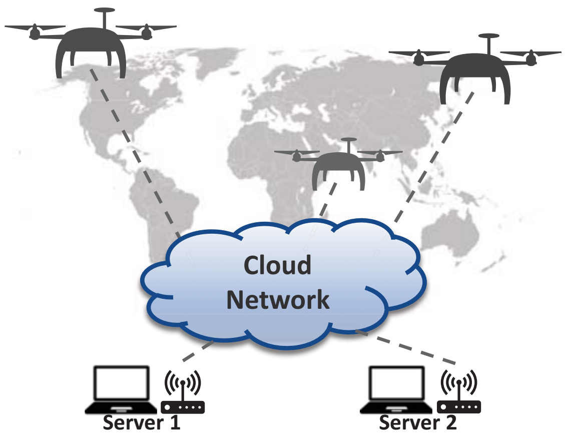

Fig. 1: Remote controlled UAVs via cloud network

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) offer promising versatility and agility to achieve a wide range of missions at low costs [1]–[4]. Many UAV applications can show more outstanding effectiveness if the UAVs are controlled over longer distance [5]. However, long distance communication increases the time delay in a network, and the irregular, long time delay may degrade the control performance due to following reasons: 1) the observed UAV state in a remote side does not match the current UAV state due to the delayed state feedback, 2) the UAV also receives the outdated control input from the remote. Nevertheless, UAV research has often ignored the negative impact of the communication delay and most experiments were performed in well-equipped communication environments such as indoor laboratories.

Networked control system (NCS) approaches have been studied to overcome the problems related to the delay. NCS is a control framework to integrate many sensors, controllers, and plants at different geographical locations and to exchange signal over communication networks [6], [7]. The most striking difference between the NCS and the other control systems is that the NCS uses a general-purpose network for various irrelevant yet concurrent applications [6], which means that the perfect communication is no longer assured.

Nonetheless, the NCS has some of the advantages: 1) it can address the network delay induced in a control loop, 2) various sensors, server, controller and plant can be connected simultaneously, and 3) it is suitable for small plants such as the UAV because it requires less computing power, small memory space by performing complicated control and utilizing a large amount of database on the server side. This mechanism is called as local simple and remote complex (LSRC).

There have been several researches that take advantage of the NCS in remote control. In [8]–[10], predictive control approaches are taken to provide a local plant with a sequence of predicted control inputs. Then, the local plant chooses a proper control input corresponding to the current network condition. These papers assume that the plant dynamics is known and simple such as a single servo motor. On the other hand, the multirotor dynamics that we are interested in is not so simple and may not be precisely known especially in the NCS setting. A small difference in the dynamics can cause an unexpected movement, or even crash in the worst case. In [11], [12], they tried to learn the network delay itself and used it for the networked control. However, both only learn the approximate tendency of network delay, thus cannot cope with the volatile delay. In [13], [14], the NCS problems for the UAV are addressed. However, both papers also assume that the plant dynamics is known, and network delays are time-invariant.

To solve problems in a more realistic environment, this study aims at establishing the NCS connecting SNU (South

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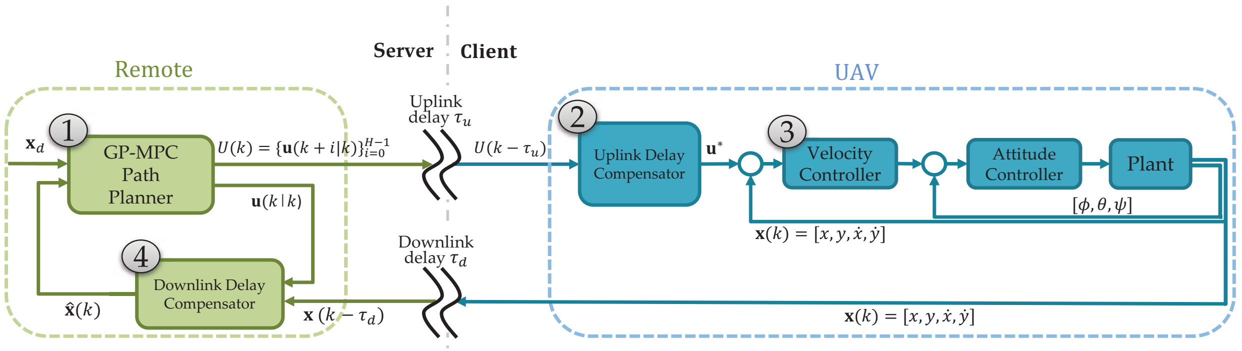


Fig. 2: The overall structure of the proposed algorithm: ① GP-MPC path planner (in server) sends control horizon $U(k)$, ② uplink delay compensator (in client) chooses proper control input $\mathbf{u}^*$ in the delayed control horizon $U(k-\tau_u)$ according to the current time, ③ UAV inner control loop (in client) performs cascade control and sends full-state observation $\mathbf{x}(k)$ of the UAV, ④ downlink delay compensator (in server) estimates the current state of UAV $\hat{\mathbf{x}}(k)$ by compensating for downlink delay

Korea) and KTH (Sweden) for a cooperative flight of the multirotor-type UAVs. We build an internet-based networked control system, and design a path planning algorithm for the multirotor against a time-varying delay as shown in Fig. 1. Considering the characteristic of the NCS, we assume that the exact plant physical properties are unknown.

The main contribution of this paper is to design the networked controller using model predictive control (MPC) for the multirotor platforms. It can cope with not only the time-varying network delay but also any type of delay due to calculation or transmission. A machine learning technique is applied to improve the control performance by learning the multirotor dynamic models. It does not learn the time delay itself but learns a multirotor's unknown nonlinear model. Thus, we do not need a precise dynamic model in advance.

We employ the Gaussian process (GP) to learn the multirotor dynamics. The GP is an algorithm that has received much attention in recent years and has been widely used in applications including the UAV control [15] and the model learning of the MPC [16], [17]. We utilize a spare GP technique with the fully independent training conditional algorithm (FITC), which is less computationally intensive than the general GP algorithm.

The remainder of this paper is organized as follows. In Section II, we propose the problem statement which will be introduced. Section III explains the plant model learning with the GP. Section IV introduces the design process of the MPC for networked UAV, and Section V details real-time experiment results. The final Section discusses the results and the control performance improvements.

II. PROBLEM STATEMENT

We present the proposed NCS configuration for a multirotor system to compensate the time-varying network delay occurring in the networked control situation. The overall structure can be divided into two parts, one on the server side and the other on the client side. In this study, the remote side is the server, and the multirotor is the client. They communicate fixed-size data, called packets, for the control loop. The uplink delay τ_u occurs when the packets are transmitted from the server to the client. The downlink delay τ_d occurs in the opposite case. To configure the NCS, we suggest a compensation method that consists of the following four parts.

- Part 1: GP-MPC for path planning (Section II.*A*)
- Part 2: uplink delay compensation (Section II.*B*)
- Part 3: UAV inner control loop
- Part 4: downlink delay compensation (Section II.*C*)

Fig. 2 shows overall structure. The MPC path planner in the server solves an optimization problem to predict a trajectory and results a control input set during H time steps. It puts the predicted control horizon in the packet with the time stamp and sends it to the client, during which the uplink time delay occurs. The uplink delay compensator calculates τ_u on the client side by comparing the time stamp when the packet was generated and the current time and sends proper control input to the UAV according to τ_u. The UAV's inner controller conducts a cascade control with the received control input and sends out a full state feedback to the server. In the server, the downlink delay compensator calculates τ_d and estimates the current state of the UAV using a control input history. Estimated values are also used in the MPC path planner again.

A. GP-MPC for path planning

Let us define the state variables of the UAV as $\mathbf{x} := [\mathbf{p}^T\ \mathbf{v}^T]^T := [x\ y\ \dot{x}\ \dot{y}]^T \in \mathbb{R}^4$. It includes the position $\mathbf{p} \in \mathbb{R}^2$ and the velocities $\mathbf{v} \in \mathbb{R}^2$ in the inertial frame. The proposed setting works in the same manner in 3-D, but we use 2-D notation for simplicity. $\mathbf{x}_d := [x_d\ y_d\ \dot{x}_d\ \dot{y}_d]^T \in \mathbb{R}^4$ is the desired position and velocities, $\mathbf{u} := [u_x\ u_y]^T \in \mathbb{R}^2$ is the control input vector. We assume that the altitude and yaw angle of the UAV are maintained by a separate controller. The reason why the state variables do not include roll and pitch angle unlike the previous works [1] is because the attitude of the UAV changes rapidly, either estimating or measuring the current roll and pitch angle in the network environment with time delay is not reasonable.

The main objective of this research is to follow the desired trajectory with minimum deviation. We use the MPC for path planning, which tries to minimize the trajectory deviation $\sum_{i=1}^{H} ||\mathbf{x}(k+i) - \mathbf{x}_d(k+i)|| \to 0$ during the look-ahead horizon H. The multirotor dynamic model $f(\mathbf{x},\mathbf{u})$ for the MPC is set as

$$\begin{aligned}\mathbf{x}(k+1) &= f(\mathbf{x}(k),\mathbf{u}(k)) \\ &= f_n(\mathbf{x}(k),\mathbf{u}(k)) + g(\mathbf{x}(k),\mathbf{u}(k)).\end{aligned} \tag{1}$$

$f_n(\mathbf{x},\mathbf{u})$ is the nominal known model which is derived in (6)−(9), $g(\mathbf{x},\mathbf{u})$ is an unknown nonlinear model, to be learned by the GP. Setting the multirotor dynamics as the sum of nominal and data-driven model via the GP improves the prediction accuracy because these models are complementary. In other words, the GP model can supplement the nominal model's residual dynamics, and the nominal model can mitigate the failure of the GP prediction because the GP tends to result a zero output when the input of the sample is not around the domain of the existing training data set [5]. Using these definitions, we obtain optimized control horizon $U(k)$ and prediction horizon $X(k)$ as

$$\begin{aligned}U(k) &= \{\mathbf{u}(k+i|k)\}_{i=0}^{H-1} \in \mathbb{R}^{2\times H}, \\ X(k) &= \{\mathbf{x}(k+i|k)\}_{i=1}^{H} \in \mathbb{R}^{4\times H}.\end{aligned} \tag{2}$$

Typical MPC executes only the first input $\mathbf{u}(k|k)$. However, to make use of the network advantage of the transmitting data packets, which can include large data sets in a single fixed-size package, a set of serial control inputs are packed and transmitted through the network at time k [10].

B. Uplink delay compensation

The client receives the packet including the control horizon and the time stamp. However, due to the uplink delay τ_u, the client receives a packet at τ_u time later than the time it was created. τ_u can be calculated by comparing the time stamp included in the data packet with the time when the client receives the packet. During this delay, the UAV is following the previous trajectory so that the current UAV state is expected to be at the predicted position $\mathbf{x}(k|k-\tau_u) \in X(k-\tau_u)$. The uplink delay compensator chooses the proper control input $\mathbf{u}^*$ in the delayed control horizon $U(k-\tau_u)$ according to the current time,

$$\mathbf{u}^* = \mathbf{u}(k|k-\tau_u) \in U(k-\tau_u). \tag{3}$$

$\mathbf{u}^*$ is given to the UAV velocity controller.

C. Downlink delay compensation

The downlink delay τ_d can be calculated by comparing the time stamp included in the data packet with the time when the server receives the packet. First we define the estimation function $f^{\{n\}}$ with a recurrence relationship using the dynamic model $f(\mathbf{x},\mathbf{u})$. The server stores the history of past control inputs $\{\mathbf{u}(k-j|k-j)\}_{j=1}^{t_0}$, and the estimation function $f^{\{n\}}$ to calculate the estimated current position $\hat{\mathbf{x}}(k)$ is given by

$$\begin{aligned}f^{\{0\}}(\mathbf{x}(k)) &\triangleq \mathbf{x}(k) \\ f^{\{1\}}(\mathbf{x}(k)) &\triangleq f(f^{\{0\}}(\mathbf{x}(k)),\mathbf{u}(k|k)) \\ f^{\{2\}}(\mathbf{x}(k)) &\triangleq f(f^{\{1\}}(\mathbf{x}(k)),\mathbf{u}(k+1|k+1)) \\ &\vdots \\ f^{\{n+1\}}(\mathbf{x}(k)) &\triangleq f(f^{\{n\}}(\mathbf{x}(k)),\mathbf{u}(k+n|k+n)) \\ &= \mathbf{x}(k+n+1), \quad (n=0,1,...)\end{aligned} \tag{4}$$

When the delayed observation $\hat{\mathbf{x}}(k-\tau_d)$ is given, $\hat{\mathbf{x}}(k)$ is calculated by the following equation:

$$\hat{\mathbf{x}}(k) = f^{\{\tau_d\}}(\hat{\mathbf{x}}(k-\tau_d)). \tag{5}$$

III. MODEL LEARNING USING GAUSSIAN PROCESS

In the previous section, we define the UAV's dynamic model $f(\mathbf{x},\mathbf{u})$ as the sum of the nominal model $f_n(\mathbf{x},\mathbf{u})$ and the unknown model $g(\mathbf{x},\mathbf{u})$. We use a linear model of the UAV for the nominal model, which was derived from [18]. We approximate the nominal model as a 1_{st} order dynamics and set the control input $\mathbf{u}$ as a desired velocity of the UAV's velocity controller, which is more stable than setting the direct control input such as a desired moment or attitude because the velocity controller is less time-sensitive than both a motor thrust controller and attitude controller. If the UAV model can be considered as a point mass model, the dynamics equation of the UAV is defined as

$$\dot{\mathbf{x}} = A_c\mathbf{x} + B_c\mathbf{u}, \tag{6}$$

$$A_c \triangleq \begin{bmatrix}0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -1/t_x & 0 \\ 0 & 0 & 0 & -1/t_y\end{bmatrix}, \tag{7}$$

$$B_c \triangleq \begin{bmatrix}0 & 0 \\ 0 & 0 \\ 1/t_x & 0 \\ 0 & 1/t_y\end{bmatrix}. \tag{8}$$

Time constants t_x and t_y in the 1_{st} order dynamics of $\mathbf{v}$ can be determined experimentally [19]. Using (6), the difference equation for discrete system can be derived as

$$\begin{aligned}\mathbf{x}(k+1) &= A_d\mathbf{x}(k) + B_d\mathbf{u}(k) \\ &= f_n(\mathbf{x}(k),\mathbf{u}(k)),\end{aligned} \tag{9}$$

where A_d and B_d in the discrete domain correspond to A_c and B_c in the continuous version, respectively.

However, using an approximated dynamic model can cause inaccurate prediction horizon $X(k)$. Erroneous prediction horizon is more harmful in the NCS because both uplink and downlink delay compensators assume that the UAV follows the prediction horizon. To generate more accurate prediction horizon, the GP learns the unknown UAV model $g(\mathbf{x},\mathbf{u})$ with state $\mathbf{x}$ and control input $\mathbf{u}$. The main downside of the GP is a computational burden. To overcome this drawback, the sparse GP was developed. The sparse GP makes it possible to reduce the runtime by making assumptions about a prior distribution. In this paper, we use the sparse GP with the fully independent training conditional algorithm (FITC), which is introduced in [20].

To learn such an unknown model $g(\mathbf{x},\mathbf{u})$ using the GP modelling techniques, we define the state control tuple $\tilde{\mathbf{x}}(k)$ and the residual model $\mathbf{z}(k)$ as follows:

$$\begin{aligned}\tilde{\mathbf{x}}(k) &= [\mathbf{v}(k)^T\mathbf{u}(k)^T]^T \in \mathbb{R}^4,\\ \mathbf{z}(k) &= g(\mathbf{x}(k),\mathbf{u}(k)) + \varepsilon\\ &= \mathbf{x}(k+1) - f_n(\mathbf{x}(k),\mathbf{u}(k)) + \varepsilon \in \mathbb{R}^4.\end{aligned} \tag{10}$$

$\tilde{\mathbf{x}}(k)$ does not include $\mathbf{p}(k)$ because it does not affect the residual model $\mathbf{z}(k)$. We assume that the output of the function $g(\mathbf{x}(k),\mathbf{u}(k))$ is corrupted by white noise ε with variance σ_n. $\tilde{\mathbf{x}}_*$ is a GP test input data and $\mathbf{z}_*$ is a GP test target data. To predict the GP test target data, we first acquire the GP training input data $\tilde{\mathbf{X}} = \{\tilde{\mathbf{x}}(i)\}_{i=1}^N$ and the training target data $\mathbf{Z} = \{\mathbf{z}(i)\}_{i=1}^N$. Then, we assume that the prior distribution of $\mathbf{Z}$ and $\mathbf{z}_*$ have a joint Gaussian distribution with zero-mean written as

$$\begin{aligned}\begin{bmatrix}\mathbf{Z}\\ \mathbf{z}_*\end{bmatrix} &\sim \mathcal{N}\left(\mathbf{0}, \begin{bmatrix}k(\tilde{\mathbf{X}},\tilde{\mathbf{X}}) + \sigma_n I & k(\tilde{\mathbf{X}},\tilde{\mathbf{x}}_*)\\ k(\tilde{\mathbf{x}}_*,\tilde{\mathbf{X}}) & k(\tilde{\mathbf{x}}_*,\tilde{\mathbf{x}}_*)\end{bmatrix}\right)\\ &= \mathcal{N}\left(\mathbf{0}, \begin{bmatrix}K_{zz} + \sigma_n I & K_{z*}\\ K_{*z} & K_{**}\end{bmatrix}\right),\end{aligned} \tag{11}$$

In this paper, the squared-exponential kernel function k is used, which is defined as

$$k(\tilde{\mathbf{x}},\tilde{\mathbf{x}}^*) = \sigma_s^2(-\frac{1}{2}(\tilde{\mathbf{x}}-\tilde{\mathbf{x}}^*)^T\Sigma^{-1}(\tilde{\mathbf{x}}-\tilde{\mathbf{x}}^*)), \tag{12}$$

where σ_s^2 is the variance of the function $g(\mathbf{x},\mathbf{u})$ and Σ is the length scale that determines how fast the correlation between data points decreases. The hyper parameters represent the smoothness of the function estimated by the GP. Typically, the hyper parameters can be learned by evidence maximization [21]. The posteriori distribution of $\mathbf{z}_*$ is derived as follows:

$$\begin{aligned}p(\mathbf{z}_*|\tilde{\mathbf{X}},\tilde{\mathbf{x}}_*) &\sim \mathcal{N}(\boldsymbol{\mu}_*,\boldsymbol{\Sigma}_*)\\ \boldsymbol{\mu}_* &= K_{*z}(K_{zz}+\sigma_n I)^{-1}\mathbf{Z}\\ &= g(\mathbf{x},\mathbf{u})\\ \boldsymbol{\Sigma}_* &= K_{**} - K_{*z}(K_{zz}+\sigma_n I)^{-1}K_{z*}\end{aligned} \tag{13}$$

We use the sparse GP to reduce the computational complexity. The sparse GP starts with the generation of the inducing input data $\tilde{\mathbf{x}}_c$ and corresponding target data $\mathbf{z}_c$. With the sparse GP algorithm and inducing GP data, the probability of $\mathbf{z}_*$ can be calculated with a lower computational cost compared with that of nominal GP model [22].

As a result, we learn the unknown model $g(\mathbf{x},\mathbf{u})$ and obtain the total dynamic equation $f(\mathbf{x},\mathbf{u})$. It is used for MPC path planning in section II.*A*, and downlink delay compensation in section II.*C*.

IV. MODEL PREDICTIVE CONTROL FOR NETWORKED UAV

In the previous section, we introduced the nominal model $f_n(\mathbf{x},\mathbf{u})$ and the GP model $g(\mathbf{x},\mathbf{u})$. We use a total dynamic model of the UAV $f(\mathbf{x},\mathbf{u})$ as the model constraint in the following MPC setup:

$$\begin{aligned}&\min_{\mathbf{u}(k+i|k),0\le i<H} J_k = ||\mathbf{x}(k+H) - \mathbf{x}_d(k+H)||_P^2\\ &+\sum_{i=0}^{H-1}(||\mathbf{x}(k+i) - \mathbf{x}_d(k+i)||_Q^2 + ||\mathbf{u}(k+i|k)||_R^2)\end{aligned} \tag{14}$$

subject to

$$\begin{aligned}\mathbf{x}(k+i+1) &= f(\mathbf{x}(k+i),\mathbf{u}(k+i|k))\\ |\mathbf{u}(k+i|k)| &\le \mathbf{u}_{max}\\ i &= 0,\cdots,H-1\\ \hat{\mathbf{x}}(k) &= f^{\{\tau_d\}}(\hat{\mathbf{x}}(k-\tau_d))\\ \mathbf{x}(k) &= \hat{\mathbf{x}}(k).\end{aligned} \tag{15}$$

Here $||\mathbf{k}||_A^2$ is a quadratic form of vector $\mathbf{k}$ with a positive semi-definite weighting matrix A. J_k is the cost function and $\hat{\mathbf{x}}(k)$ is the estimated state obtained in the downlink delay compensator described in section II.*C*. The MPC calculates the state transition up to the look-ahead horizon of H steps. The positive semi-definite matrices P, Q, and R are weights for the final state error, i_{th} state error, and control input, respectively. The vector $\mathbf{u}_{max}$ denotes the constraint of control input. The results of the MPC are signals defined in (2).

To solve for the optimal control problem in real time, a stable and fast optimal control solver is required. We use a Sequential Linear Quadratic (SLQ) solver whose speed and performance were previously demonstrated in agile flight experiments [23]. The discrete-time dynamic model (1) can be easily computed from the continuous dynamics using the Euler's method. The detailed algorithm of SLQ for the MPC is shown in [24].

In section II.*C*, the downlink delay compensator uses $\mathbf{u}(k-i|k-i)$ to transfer $\mathbf{x}(k-i)$ to the next step $\mathbf{x}(k-i+1)$ in each $k-i$ time step. However, $\mathbf{u}(k-i|k-i-\tau_u) \in U(k-i-\tau_u)$ was actually used as a result of the uplink delay compensator, and the downlink delay compensator does not know τ_u because it varies every moment. The best strategy is to make $\mathbf{u}(k+i|k)$ and $\mathbf{u}(k+i|k-1)$ as close as possible. As a result, the server can choose the $(k-i)$-th step control input with minimum difference from the actual control input used. To consider this changes to the MPC constraints, we redefine the cost function of (14) as follows:

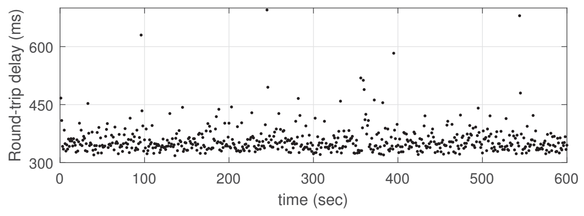
$$\begin{aligned}&\min_{\mathbf{u}(k+i|k),0\le i<H} J_k = ||\mathbf{x}(k+H) - \mathbf{x}_d(k+H)||_P^2\\ &+\sum_{i=0}^{H-1}(||\mathbf{x}(k+i) - \mathbf{x}_d(k+i)||_Q^2 + ||\mathbf{u}(k+i|k)||_R^2)\\ &\qquad+\sum_{i=0}^{H-2}(||\mathbf{u}(k+i|k) - \mathbf{u}(k+i|k-1)||_S^2)\end{aligned} \tag{16}$$

Even though the inclusion of the last term decreases the optimal performance, it increases stability which is a more critical factor in networked control systems.

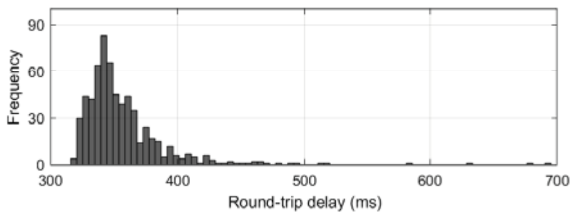
V. FLIGHT EXPERIMENT

A. Delay analysis

This subsection shows the result of the network delay characteristics analysis between Korea and Sweden. It was confirmed that the network communication between Korea and Sweden is on average 20 nodes. The delays that occur at each node can be seen to follow the Poisson distribution. Thus, we can assume that the round-trip network delay which is a sum of each node delay follows the normal distribution according to the central limit theorem even though they have different parameters. Fig. 3 supports that our assumptions. For a fair comparison with each experiment, we set the artificial delays τ_u and τ_d to follow the normal distribution $\mathcal{N}(0.5, 0.1)$ with a random seed.



(a) Round-trip delay



(b) Histogram

Fig. 3: Delay analysis between SNU (South Korea) and KTH (Sweden) (a) round-trip delay during 600 seconds (b) histogram of the round-trip delay

B. Experimental setup

We validated the effectiveness of the proposed framework through actual flight experiments. The experimental setup is illustrated in Fig. 4. We use the Crazyflie 2.0 multirotor developed by Bitcraze [25], whose weight is approximately 32 g and maximum takeoff weight is 42 g. Position of the multirotor is measured by a VICON motion capture system operating at 100 Hz and all the other states are estimated using Kalman filter from the position information. We use a server computer with Intel i7 6700K 4.0GHz CPU and Robot Operating System (ROS). The server computer solves the MPC and sends the predicted control horizon to the multirotor. The MPC look-ahead horizon H is set to 20, and the MPC sampling time is 0.1 seconds. The constraint on the control input is given by $\boldsymbol{u}_{max} = [0.6\ 0.6]^T$.

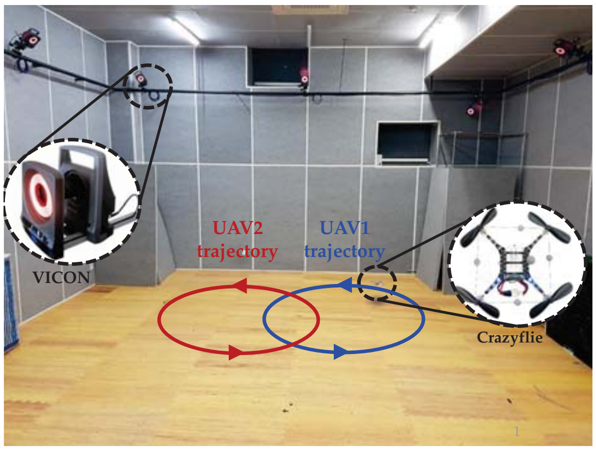


Fig. 4: A snapshot of the experimental setup of the trajectory tracking control with NCS configuration

Experiment 1: tracking control with a single multirotor

In this experiment, we conducted the path tracking control experiment in the presence of both uplink delay and downlink delay. We give a circular desired path with period 10 seconds, radius 0.5 meters. Fig. 5 shows the results of our first experiment, which compares three cases: (a) tracking control without any delay compensation, (b) the proposed delay compensation algorithm without the GP model learning, (c) the proposed delay compensation algorithm with the GP model learning. Even though the prior information of the time delay is not given to the delay compensator, tracking control performances of (b) and (c) are satisfactory because of the robustness of the proposed algorithm. Especially the learned GP model enhances the control performance because of more accurate prediction horizon and downlink delay compensation. Table I shows the comparison of tracking performance.

TABLE I: RMSE corresponding to given trajectory

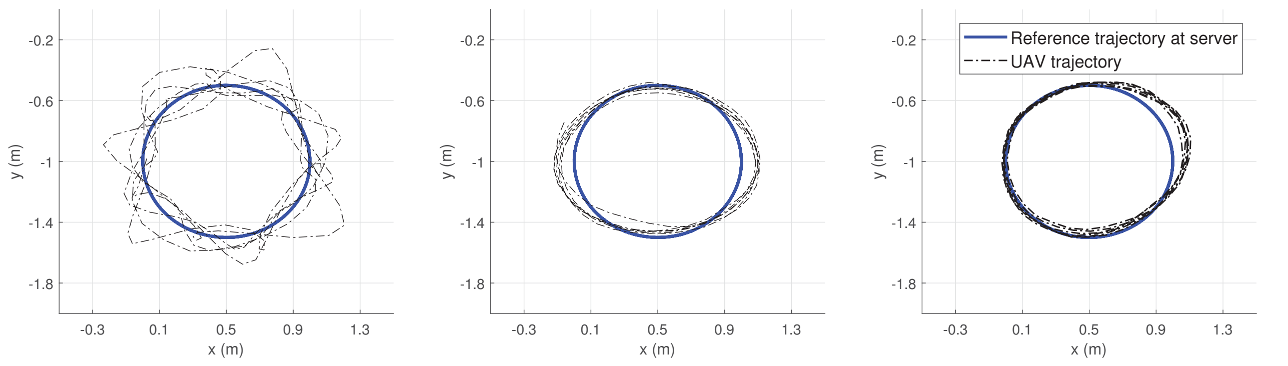
	Exp 1-(a)	Exp 1-(b)	Exp 1-(c)
x RMSE	0.1048	0.0807	**0.0507**
y RMSE	0.0861	0.0495	**0.0350**
(x, y) RMSE	0.1352	0.0946	**0.0616**

Experiment 2: cooperative path tracking with two multirotors

In this experiment, we conducted the cooperative path tracking control with two multirotors. We assume a scenario where each multirotor is manipulated in different locations. Thus we set the both artificial delays τ_u and τ_d to follow the normal distribution $\mathcal{N}(0.5, 0.1)$ and $\mathcal{N}(0.3, 0.05)$ for each multirotor. We give a circular desired path with period 10 seconds, radius 0.5 meters. The two multirotors fly a half meter apart in x-axis. Fig. 6 shows the results of our second experiment, which compares two cases: (a) cooperative tracking control without any delay compensation, (b) cooperative tracking control with the proposed delay compensation algorithm and the GP model learning. Even though the network delays of each multirotor are different, the proposed algorithm maintained the given distance compared to the result without compensation algorithm.

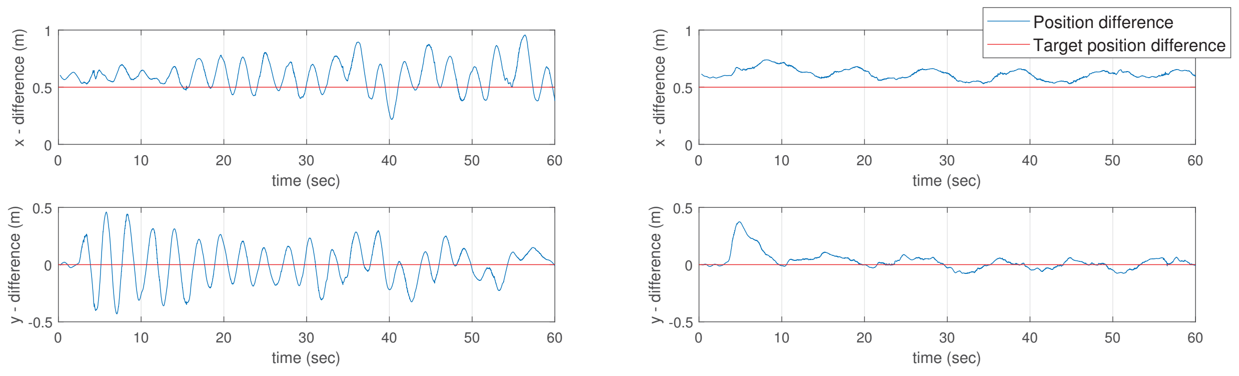
VI. CONCLUSIONS

This paper presented a configuration of NCS for the UAV to compensate the time-varying network delay. The NCS



(a) without compensation (b) with compensation, without GP learning (c) with compensation, with GP learning

Fig. 5: Experiment 1 : path tracking control of the single multirotor



(a) without compensation (b) with compensation and with GP learning

Fig. 6: Experiment 2 : cooperative tracking control of two multirotors with different network delays. The blue line represents the distance difference of each multirotor. The closer the blue line is to the red line, the better.

structure proposed in this paper consists of 4 parts: GP-MPC path planner, uplink delay compensator, UAV inner-loop controller, and downlink delay compensator. This structure was configured to compensate the network delay and control the multirotor efficiently. We also used the GP model learning to improve the delay compensation performance and MPC path planning accuracy. The first experiment on tracking control of the multirotor UAV confirms that the control performance was improved. The second experiment on cooperative path tracking control of the two multirotors shows that the proposed algorithm can cope with unknown network delays.

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