Formation flight control under communication failure

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***Abstract*—This paper presents the management of UAV formation flight with respect to varying levels of communication among UAVs. Inter-vehicle communication in the formation is a critical issue because each UAV needs the information on other vehicles for formation. However, since communication is not perfect in reality, the formation performance under communication failure has to be analyzed. This study uses position data measured by sensors for overcoming communication failures in the standard leader-follower structure formulated in the nonlinear model predictive control(NMPC) framework. The perceived and obtained position data of each UAVs through GPS or sensor are noisy. These are estimated by extended Kalman filter. The numerical simulation results support the feasibility of the proposed formation flight method.**

I. Introduction

Recently, formation flight control has received considerable interests especially in maintaining formation and guiding each UAV for a formation position.

For the formation architecture, the leader-follower-based architecture used in this paper is studied most often. In this approach, one vehicle is set to be a leader and others are designated as followers, i.e., wingmen. The leader supplies the nominal trajectory for formation flight.

In general, the formation structures mentioned above require communication between UAVs in the formation, because they need the position data of other vehicles to track the leader or to avoid other vehicles. Most researches assume that communication is perfect and achieve the formation maneuver [7,8].

However, this assumption is really ideal, and this communication failure may lead to formation breakdown, the case study for the communication failure has to be done. Some studies consider communication failure, but it is partial failure [9,10], i.e., the vehicles which have a communication system exchange the data using the unbroken part of the communication system, therefore, they still communicate each other.

On the other hand, this paper studies how to make formation under communication failure or without an inter-vehicle communication system, using sensor data only. In addition, it is assumed that all data used in the formation contain the process or measurement noise. This is more realistic than deterministic data, because information is obtained by sensors such as gyro, IMU or GPS. These corrupted data are estimated by Extended Kalman filter(EKF).

A formation controller, in this study, is designed by numerically efficient nonlinear model predictive tracking control (NMPTC) algorithm from [2], which solves a finite horizon open-loop optimal control problem on-line. Since NMPTC is used on-line, it is advantageous that if some disturbances or obstacles suddenly appear, the adapted control law can be produced.

In many studies, inequality constraints for control input and state saturation have been considered using various methods, for instance, trimming over saturation value, heavily weighting each state or input over saturation, or using positive definite matrices and Euclidean norms in LMI setting. Instead, this research uses Karush-Kuhn-Tucker condition for inequality constraints [3]. This scheme is more reliable than simple trimming as discussed in [4].

This paper begins with a description of multi-UAV dynamic model and formation control problem in Section 2. Section 3 reviews the NMPC algorithms for this problem with the inequality constraints for control input and states saturation. Section 4 describes the guidance law using relative distance and the leader's own angles, and explains how to keep the formation without communication. Section 5 presents the numerical simulation results of the proposed idea and the performance of sensor-based formation is evaluated in comparison with the communication-based formation flight. Section 6 gives conclusions.

II. UAV Model

The problem is to generate formation flight trajectories from the random initial locations of multiple UAVs, which keep each wingman at a desired distance from the leader. We use the following two-dimensional (2-D) point mass model for UAVs:

$$\dot{\mathbf{x}} = f_c(\mathbf{x}, \mathbf{u}) \ + \mathbf{w}(\mathbf{t}) \tag{1}$$

where $\mathbf{x} = [V \ \psi \ x \ y] \in \Re^4$, $\mathbf{u} = [u_1 \ u_2] \in \Re^2$, x and y represent position in the inertial frame, V and ψ denote velocity and heading angle, respectively. Control inputs u_1 and u_2 represent forward and lateral acceleration. It is assumed that

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the control input is transmitted to the plant without any lag.

Only for controller design purposes, we discretize Eqn. (1) to

$$\mathbf{x}_{k+1} = f_d(\mathbf{x}_k, \mathbf{u}_k) + \ \mathbf{w}_k \tag{2}$$
$$f_d(\mathbf{x}_k, \mathbf{u}_k) \triangleq \mathbf{x}_k + T_s f_c(\mathbf{x}_k, \mathbf{u}_k)$$
$$\mathbf{w}_k \triangleq T_s \mathbf{w}(t)$$
$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k$$

where T_s is the sampling time and $\mathbf{H}$ is the measurement matrix, $\mathbf{w}$ and $\mathbf{v}$ are the process and measurement noise. For the simplicity, we assume that $\mathbf{x}(0) \sim N(\bar{\mathbf{x}}_0, P_0)$, $\mathbf{w}_k \sim N(0, \mathbf{W})$ and $\mathbf{v}_k \sim N(0, \mathbf{V})$, where $\mathbf{w}_k$ and $\mathbf{v}_k$ are white and uncorrelated with each other and with $\mathbf{x}(0)$.

III. Nonlinear Model Predictive Tracking Control for UAVs

This section describes the optimal control problem we consider and the algorithm for the optimization, considering control input saturation.

A. Optimal control problem formulation

The nonlinear model predictive tracking control(NMPTC) problem studied in this paper is as follows:

Find a control input sequence $\quad \mathbf{u}(= [u_0, u_1, \cdots, u_{N-1}])$

which minimizes

$$J = \phi(\tilde{\mathbf{y}}_N) + \textstyle\sum_{k=0}^{N-1} L(\tilde{\mathbf{y}}_k, \mathbf{u}_k)$$
$$\phi(\tilde{\mathbf{y}}_N) = \tfrac{1}{2}\tilde{\mathbf{y}}_N^T P_0 \tilde{\mathbf{y}}_N \tag{3}$$
$$L(\tilde{\mathbf{y}}_k, \mathbf{u}_k) = \tfrac{1}{2}\tilde{\mathbf{y}}_k^T Q \tilde{\mathbf{y}}_k + \tfrac{1}{2}\mathbf{u}_k^T R \mathbf{u}_k$$

where $\tilde{\mathbf{y}} = \mathbf{y}_d - \mathbf{y}, \mathbf{y} = C\mathbf{z} = [x \ y]$ and $\mathbf{y_d}$ represents the desired output of each UAV.

The dynamics of the UAVs in Eqn. (2) is regarded as equality constraints subject to inequality constraints for control input saturation in the following form:

$$|\mathbf{u}_k| - \mathbf{u}_{max} = q_u(\mathbf{u}_k) \leq 0 \tag{4}$$

B. Optimization algorithm

In general, the optimization problem defined above is difficult to solve because all constraints need to be considered simultaneously. We incorporate the above constraints into the original cost function in Eqn. (3) using Lagrange multipliers and Karush-Kuhn-Tucker variables. The augmented cost function is as follows :

$$J_a = \phi(\tilde{\mathbf{y}}_N) + \textstyle\sum_{k=0}^{N-1} \Big[L(\tilde{\mathbf{y}}_k, \mathbf{u}_k) + \lambda_{k+1}^T (f_k - \mathbf{x}_{k+1}) + \textstyle\sum_{j=1}^{n_u} \mu_{u_j} q_{u_j}(\mathbf{u}_k)^T Q_j^c(q_{u_j}) q_{u_j}(\mathbf{u}_k) \Big] \tag{5}$$

where

$$Q_j^c(q_{*_j}) = \begin{cases} 0 & q_{*_j}(\cdot) \leq 0 \\ 1 & \text{otherwise} \end{cases} \tag{6}$$

and n_u represents the number of control inputs.

The augmented performance index is minimized at each discrete time k using the algorithm of the Ref.2.

IV. Formation Architecture

This section describes the formation architecture. Subsection A introduces the implementation structure of formation flight used in this research, i.e., the leader-follower-based decentralized architecture, and the guidance law based on the leader's own heading and position information. In Subsection B, communication-based formation flight is addressed, whose data is estimated by extended Kalman filter (EKF). Subsection C considers sensor-based formation flight under the communication trouble. Finally, Subsection D briefly comments the method of the state estimation using the EKF.

A. Leader-follower-based decentralized formation flight

The leader-follower-based formation flight is studied most often. In this approach, one vehicle is set to be a leader and others are designated as followers, or wingmen. The leader supplies the reference trajectory for formation flight.

In considering real-time implementation, the NMPC can be implemented in two settings: centralized and decentralized schemes. Centralized methods treat all vehicles as a single entity. If each vehicle has two control inputs, six control inputs in total are produced simultaneously in the formation structure composed of three vehicles. This property leads centralized methods to have better performance than decentralized methods [4]. However, since this method is based on the communication system among all the vehicles, this is not suitable when communication links are broken. On the other hand, in the decentralized method, each vehicle computes its control policy using current step information from other vehicles [4].

B. Communication-based formation flight

Regardless of the implementation method shown in the Sec 4.A, each UAV in the formation needs the information about the leader. This information can include velocity, its own attitude angles and position data, etc. In many studies, it is assumed that this information is transmitted to other vehicles through communication systems. This assumption is critical for the formation maneuver because each vehicle decides its own control policy with other vehicles' state information. Furthermore, since the prediction of future states is necessary, the information transmitted to other vehicles needs to include its own control policy or its all future states. In addition, due to the process and measurement noise of the states, the communicated data are estimated by the EKF.

C. Sensor-based formation flight

Sensor-based formation means that the followers track the leader using the data obtained by the onboard sensors such as radar or camera. In this data-based formation flight, each UAV is equipped with one EKF. If the communication system is broken, all UAVs come to have several EKFs, i.e., the number of EKFs matches the number of UAVs ranging in the sensor, assuming that all the UAVs in the sensing range have the same dynamics. The NMPC technique used in this study needs state prediction to optimize control policy. Therefore, it predicts other vehicles' future states using the current estimated information for the optimization algorithm. The procedure of sensor-based formation flight follows as below

Step 1 : Solve each optimization problem as mentioned in Sec. 3. A.

Step 2 : Progress one step using the solved optimal control policy and one-step-advanced information are taken by the sensor immediately.

Step 3 : Each vehicle estimates its own state vector and other vehicles' states in the sensor range using EKF.

Step 4 : Predict the future state behavior, and goto *Step* 1.

D. State Estimation

The basic step for the estimation follows the formula of the extended Kalman filter (EKF) in the Ref. 5.

Having developed a model for the observations, we initialize the EKF. At first, *a priori* state and error covariance are required in the following form

$$\hat{\mathbf{x}}^{-}(0) = \mathrm{E}\left[\mathbf{x}(0)\right] \tag{7}$$

and

$$P^{-}(0) = \mathrm{Cov}\left[\mathbf{x}(0) - \hat{\mathbf{x}}^{-}(0)\right] . \tag{8}$$

In this study, we take two measurements $\mathbf{z}(0)$ and $\mathbf{z}(1)$ and use them to approximate each vehicle's own states and other vehicles' own behavior. In this case, we must wait for two observations before starting the EKF. In case of each vehicle's own states estimation, the initial states of the EKF are chosen as the midpoint of the two measurements as follows

$$\hat{\mathbf{x}}^{-}(0) = \left[\ (\mathbf{z}(0) + \mathbf{z}(1))/2\ \right] . \tag{9}$$

However, in the other vehicles' estimation, since just the position data are acquired, the initial states of the EKF are chosen as belows:

$$\hat{\mathbf{x}}^{-}(0) = \begin{bmatrix} \sqrt{(z_1(1) - z_1(0))^2 + (z_2(1) - z_2(0))^2}/T_s \\ cos\left(\frac{z_1(1) - z_1(0)}{\sqrt{(z_1(1) - z_1(0))^2 + (z_2(1) - z_2(0))^2}}\right)^{-1} \\ (z_1(0) + z_1(1))/2 \\ (z_2(0) + z_2(1))/2 \end{bmatrix} . \tag{10}$$

where z_1 and z_2 denote first and second elements of the measurement.

Error covariance matrix P must be positive-definite. Therefore, in order to ensure the positive definiteness, P is chosen like

$$P^{-}(0) = \lambda I, \quad \lambda > 0$$

instead of the Eqn. (8).

V. Numerical Simulations

This section presents simulation scenario and results. The simulation described here uses one leader and two wingmen under the leader-follower-based decentralized scheme described in Sec. III-A. The leader with the initial position (0,0) is commanded to follow the reference trajectory that consists of level flight and steady turn.

The desired horizontal and vertical distance among the leader and all wingmen is set to 50 m. A finite horizon for NMPTC is set to 50 and sampling is 10Hz. And total simulation time is set to 150 seconds. In addition, it is assumed that position accuracy of each vehicle's GPS receiver and radar sensor is below five meters and ten meters, respectively. These values are referred from a single point L1 receiver, Superstar II manufactured by Novatel Inc. and ka-band collision-avoiding radar system manufactured by STX Engine in Korea.

In order to show the performance against communication failure, the simulation assumes that the communication system is broken after 30 seconds. After that, the followers track the leader using the sensing data. The result of sensor-based formation is compared with that of communication-based formation in terms of total cost and computation time.

In the aspects of the sensing, it is assumed that each UAV can measure its own velocity, heading angle and position while the capability of the sensor is restricted to the position detection. In the communication-based case, each vehicle knows estimated data of all the other vehicles, while it directly estimates other vehicles' information using the position data in sensor-based formation. As shown in Table 1, communication-based formation achieves a slightly smaller total cost than sensor-based formation and spends less computation time. This is caused by the quantity of the measurement. Originally, the sensor perceiving specific objects measures their position data, then other information is computed and estimated using this measurement. Therefore, the communicated information of other vehicles is more accurate than the estimated data using the sensor because the transmitted data are estimated by measuring all of the states in each vehicle. It leads better performance than the sensor-based formation.

TABLE I
THE PERFORMANCE COMPARISON

	Communication-based	**Sensor-based**
Total cost	1	1.0328
Total computation time	1	1.1297

Basically, NMPC optimizes control input policy at each time step. The optimization is finished when the variation of cost value is smaller than the specific ϵ. Therefore, if the state variables used in the optimization are less accurate, the optimization needs more computation time for overcoming this impreciseness. As shown in Table 1, the tracking and computation time performance of sensor-based formation are slightly larger than those of the communication-based formation setup. However, their values are still satisfactory for real applications.

As shown in Fig. 1, all the relative distance error between the leader and wingmen are kept within the admissible range. Although the relative distance formation based on the communication system is more accurate than in the sensor-based formation, it is noteworthy that the relative distance can be

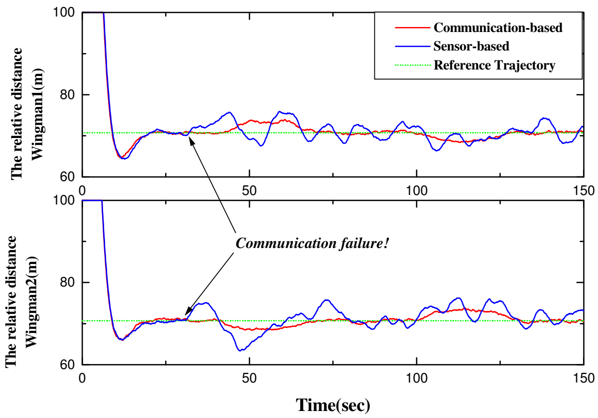

Fig. 1. The generated relative distance between the leader and wingmen

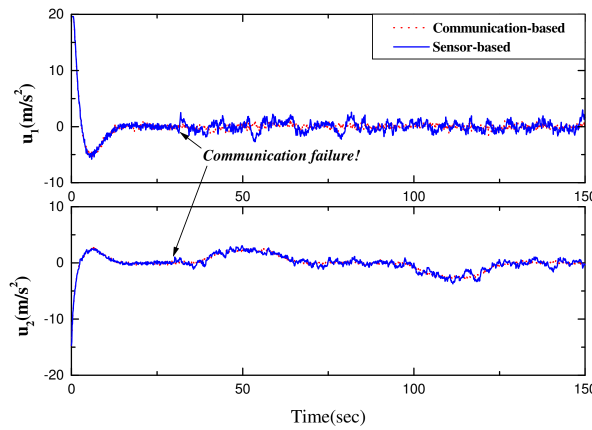

Fig. 2. Control input history of the wingman 1

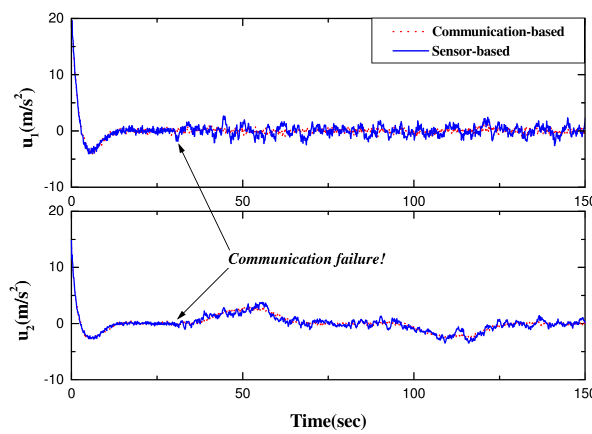

Fig. 3. Control input history of the wingman 2

preserved even under the communication failure and the error is negligible in the aspects of the formation flight.

Fig. 2 and 3 present the optimal control history of the wingmen, which confirm that the inequality constraints used in this study are satisfied. The choice of Karush-Kuhn-Tucker variables is very important, so we followed the heuristic adapting rule described in Ref. 4. In the profile of control history, because the communication system is broken at 30 seconds, we notice that the control input starts to chatter more after the communication trouble in order to cope with the data inaccuracy. This control input chattering results from the fact that the dynamic system we consider has the stochastic components [6].

VI. Conclusion

In this paper, the performance of communication- and sensor-based formation flight has been validated in the aspects of the tracking accuracy and the computation time in a nonlinear model predictive framework. We have added the process and measurement noise to the formation framework for more realistic situations. Several extended Kalman filters have removed this noise effectively enough to follow the leader. Even though the communication-based architecture achieves the slightly smaller total cost, the sensor-based method employed in this research shows the satisfactory performance in maintaining formation.

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