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Use of Risk as a Metric for Autonomous Aerial Vehicles' Adaptive Controls

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Standard optimal control algorithms work with a fixed control cost function that minimizes the control effort to achieve system stability. Similarly, robust controllers are used to mitigate differences between controller models and real-life controllers. In autonomous vehicles, the deciding agent might not know how to account for outright failures of control surface machanisms. This paper builds upon previous, and parallel work to create a consistent method that develops fault detection in autonomous aerial vehicles and uses those probabilities to develop a controller to minimize the system failure. This paper describes the background and equations that are used in this method, and then provides examples of the effects of this approach in an Ultrastick 120 simulation.

I. Nomenclature

Δt = Time step size (assumed seconds)
n = Time step n
$\vec{x}_n$ = System state at time "n"
$\hat{\vec{x}}_n$ = Estimated system state at time "n"
$\vec{y}_n$ = Observation at time "n"
$\vec{u}_n$ = Control value at time "n"
J = Control cost
Δt = The discrete time step
ϕ_{1_n} = The state's state transition matrix at time "n"
ϕ_{2_n} = The controller's state transition matrix at time "n"
Q_n, R_n, N_n = Controller cost function matrices at time "n"
C_n, D_n = Linear observation dynamics at time "n"
K_n = State-space control gain at time "n"
l_n = Risk value at time step "n"
$\vec{c}^T\left(\vec{x}_n\right)$ = Cost of an unwanted event given the system state.
$\vec{p}\left(\vec{x}_n, \vec{u}_n\right)$ = Probability of an unwanted event given the state and control

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II. Introduction and Motivation

There has been an increase in the interest of autonomous and personal air vehicles for use over dense human environments [Ref 1-3]. This interest brings with it a more pronounced set of challenges for the development and deployment of fleets of autonomous or semi-autonomous air vehicles. One of those challenges is accounting for the potential of a control surface or system failure.

Recent work in this area [Ref 4-6] describe the potential for methods to detect faults in dynamic systems, and what to do once those faults have been detected. This paper is an expansion upon fault detection methods for UAVs, and determines how to automatically account for loss of controllability of the craft due to control surface faults.

III. Background

Linear optimal control methods are well known and developed [Ref 12-16]. The measure of this optimal control is typically some control effort. The optimization finds the controller gains that maintain system stability with the minimum amount of control input. For this portion and the remainder of the paper we assume a digital control system where the control input is constant over the time period Δt. The basic dynamic equation is given in Eq. (1).

$$\begin{aligned} \vec{x}_{n+1} &= \phi_{1_n}\vec{x}_n + \phi_{2_n}\vec{u}_n \\ \vec{y}_n &= C_n\vec{x}_n + D_n\vec{u}_n \end{aligned} \tag{1}$$

We attempt to minimize the generic cost function Eq. (2) in an infinite time horizon.

$$J = \sum_{n=0}^{\infty}\left(\vec{x}_n^T Q_n \vec{x}_n + \vec{u}_n^T R_n \vec{u}_n + 2\vec{x}_n N_n \vec{u}_n\right) \tag{2}$$

Giving Eq. (3) and Eq. (4)

$$\hat{\vec{x}}_n = C_n^{-1}\left(\vec{y}_n - D_n\vec{u}_n\right) \tag{3}$$

$$\vec{u}_n = -K_n\hat{\vec{x}}_n \tag{4}$$

Which gives the optimal control gain from Eq. (5)

$$K = \left(R + \phi_2^T P \phi_2\right)^{-1}\left(\phi_2 P \phi_2 + N^T\right) \tag{5}$$

With P being the solution of the algebraic Riccati equation (Eq. (6))

$$P = \phi_1^T P \phi_1 - \left(\phi_1^T P \phi_2 + N\right)\left(R + \phi_2^T P \phi_2\right)^{-1}\left(\phi_2^T P \phi_1 + N^T\right) + Q \tag{6}$$

What we will do in this paper is show how to use a quadratic equation for risk in this system

IV. Risk-Based Optimal Control

The section above describes the basic optimal control gain for a linear, discrete system with infinite time horizon. We now look at the objective function itself. The objective of risk [Ref 7-10] is a non-linear function that can be made to guarantee a minimum by Eq. (6).

$$J = \sum_{n=0}^{\infty}\left(l_n^2\right) \tag{6}$$

In order to put this in a form that we can use, we linearize the risk function, and then square the result (Eq. (7)).

$$L = \vec{x}^T \left(\frac{\partial l_0}{\partial \vec{x}} \right)^T \left(\frac{\partial l_0}{\partial \vec{x}} \right) \vec{x} + \vec{u}^T \left(\frac{\partial l_0}{\partial \vec{u}} \right)^T \left(\frac{\partial l_0}{\partial \vec{u}} \right) \vec{u} + 2\vec{x}^T \left(\frac{\partial l_0}{\partial \vec{x}} \right)^T \left(\frac{\partial l_0}{\partial \vec{u}} \right) \vec{u} \tag{7}$$

This is now in the form that can be used with the standard linear optimal controls.

A. Risk function

Our risk function *l*, for this paper is defined as the potential expected downside (Eq. (8)).

$$l_n = \vec{c}^T \left(\vec{x}_n \right) \vec{p} \left(\vec{x}_n, \vec{u}_n \right) \tag{8}$$

The cost function is a function of the potential state, but we will assume that is a constant value, where an unwanted event is given a fixed cost amount. This gives the partial derivatives giving the values of *Q*, *R*, and *N* to be scaled components of the derivatives on the probability function. Thus, the partial derivatives of the non-linear cost function are given in Eq. (9).

$$\begin{aligned} \frac{\partial l_n}{\partial \vec{x}} &= \vec{c}^T \frac{\partial \vec{p}}{\partial \vec{x}} \\ \frac{\partial l_n}{\partial \vec{u}} &= \vec{c}^T \frac{\partial \vec{p}}{\partial \vec{u}} \end{aligned} \tag{9}$$

Previous work [Ref 7-8] details the probability of failure given the system state, but a paper by Kotilkalpudi and Williams [Ref. 11] describes the risk associated with control failure, and how it can be calculated.

With that paper, and the current formulation we can now create an optimal controller that accounts for both mission failure risk as well as loss of controllability.

V. Example Scenarios

In this section we will show how probability of faults modify the control system capabilities of UASs and UAVs. Two examples with two different fault types will be investigated. Both examples will assume the UltraStick 120 platform [Ref 17]. Both will show control results from traditional methods compared to the risk-based adaptive controller gains.

A. Loss of Aileron

This section will describe the effect of loss of an aileron has on the controllability of the UltraStick. The first portion of this section will show how the system responds to loss of this component without a risk-based controller.

The next section will show the results from the methodology presented above. Comparisons will show how as the risk of system failure increases, the system automatically transitions to use of nominal control surfaces.

B. Loss of Elevator and Aileron

This section will be structured just like the previous example. However, now the system's fault is such that controllability cannot be maintained. However, this section will show how the risk-based objective allows for the system to be stabilizable. Examples of system response in a nominal controller will be shown as will the risk-based objective response.

VI. Conclusions and Future Work

This will contain conclusion that can be drawn from the work, and future directions that the researchers might take. The initial work indicates that using the risk of system failure to automatically adjust the controller gains allows for a smoother transition for the pilot or system. The methodology also allows the pilot (computer or human) to maintain controllability or stability of the craft in case of a fault.

Future work will show how developing a guidance solution based upon situation risk and probability of system failure can be incorporated in a consistent guidance, navigation, and control framework.

References

[1] Federal Aviation Administration, *FAA Aerospace Forecast*, TC20-0011

[2] Dorr, L., "Fact Sheet – General Aviation Safety", Federal Aviation Administration, July 30, 2018, https://www.faa.gov/news/fact_sheets/news_story.cfm?newsId=21274 [cited May 12, 2020]

[3] Cobb, T., "In Major U.S. Cities, E-Commerce's 'Last Mile' Really is 6 to 9 miles", CBRE, Aug. 23, 2017, https://www.cbre.us/about/media-center/in-major-us-cities-e-commerces-last-mile-really-is-6-to-9-miles [cited May 12, 2020]

[4] Danowsky,B., Kotikalpudi, A., and Seiler, P., "Developing a certifiable UAS reliability assessment approach through algorithmic redundancy: Phase I SBIR Program Final Technical Report," Systems Technology Inc., Hawthorne, CA, 2017.

[5] V. Venkatasubramanian, V., Rengaswamy, R., Yin, K., and Kavuri, S.N., "A review of process fault detection and diagnosis Part I: Quantitative model-based methods," *Computers & Chemical engineering 27(3),* pp. 293-311, 2003.

[6] Freeman, P., Pandita, R., Srivastava, N., and Balas, G., "Model-Based and Data-Driven Fault Detection Performance for a Small UAV," *IEEE/ASME Transactions on Mechatronics Vol. 8 ,* 2013.

[7] Williams, E. A., Jin, Y., and Schulze, P. C., "Development of Probability Fields for Collision Avoidance," *AIAA AVIATION Conference,* June 15-19, Online, 2020.

[8] Williams, E., and Jin, Y., "Use of Situation and Risk Modeling in Guidance Solutions", *IEEE/ION Position Location and Navigation Symposium*, Vol. 1, IEEE, Monterey, CA, 2018, pp. 516-521.
doi: 10.1109/PLANS.2018.8373421

[9] Williams, E., and Jin, Y., "Low Earth Orbit Debris Avoidance Using Situation-Risk Assessment Modeling", *2018 AIAA SPACE Forum*, Vol. 1, AIAA, Orlando, FL, 2018.
doi: 10.2514/6.2018-5232

[10] Williams, E., and Jin, Y., "Dynamic Probability Fields For Risk Assessment and Guidance Solutions", *Annual of Navigation*, Vol. 26, No. 1, Jul. 2019, pp. 33-45.
doi: 10.1515/aon-2019-0004

[11] Kotikulapudi, A., Willilams, E. A., and Seiler, P., "…", *2021 AIAA SciTech Forum*, Jan. 11-15, Nashville, TN, 2021. (*unpublished*)

[12] Bryson, A. C., and Ho, Y.C., *Applied Optimal Control*, Glinn and Company, Waltham, MA, 1969.

[13] Gelb, A (editor), *Applied Optimal Estimation*, The M.I.T. Press, Cambridge, MA, 1974.

[14] Kirk, D. E., *Optimal Control Theory: An Introduction*, Dover, United States, 1998.

[15] Stengel, R. F., *Optimal Control and Estimation*, Dover, United States, 1994.

[16] Ben-Asher, J. Z., *Optimal Control Theory With Aerospace Applications*, AIAA press, Reston, VA, 2009.

[17] Kotikalpudi, A., "Nonlinear Simulation Model for UltraStick 25e UAS," STI WP-1457-02, Systems Technology, Inc., 2017 (unpublished).