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Missile Autopilot Design using Adaptive Nonlinear Dynamic Inversion

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Abstract—**This paper describes the continuing project Adaptive Nonlinear Dynamic Inversion (ANDI). The ANDI autopilot uses non-linear dynamic inversion with an adaptive element to account for any errors in the inversion. A reference model is included to provide the desired output performance. This allows the missile performance to be tuned by simply adjusting the reference model parameters. This will result in a design that is robust with respect to aerodynamic modeling inaccuracies and to extenal disturbances.**

I. INTRODUCTION

The typical missile autopilot use gain scheduling where the gains are designed using system linearization and linear methods. There are some problems when using the method. Gain scheduling assumes that flight condition changes slowly. When flight condition changes rapidly, the resultant autopilot may not possess the stability properties of the linear control designs displayed at their local flight conditions. System modifications or significant payload variations would require an autopilot design for each contingency.

The nonlinear autopilot design (ANDI) presented in [1] and this paper is based on the work presented in [2],[3]. ANDI does not involve gain scheduling, it uses dynamic inversion (DI) to account for changes in the missile dynamics with flight condition. Since DI is not robust to modeling errors, ANDI includes an adaptive control element with an artificial neural network (ANN). The ANN is designed to correct those errors as well as other small magnitude errors. A reference model is used to provide the idealized closed-loop behavior for the missile system. The response of the reference model to the desired acceleration commands is measured and the autopilot controls the missile to mimic that response. Pseudo control hedging (PCH) is included to avoid actuator saturation which may result in incorrect ANN learning [4]. PCH uses an actuator model with rate and position saturations to estimate the actual response of the fins to the fin commands. The difference between the achieved and the commanded fin deflections can then be used to adjust the behavior of the reference model when it identifies a response that is too aggressive for the actuators.

II. ANDI

The ANDI autopilot is designed to cover the entire flight envelope without gain scheduling. Variation of parameters in the DI allows the designer to control the shape of the response at different flight conditions. When the dynamic pressure is high, such as at low altitude and high Mach, changes in the parameters allow a more aggressive missile response than when the dynamic pressure is much lower. Parameter selection will be a much simpler and less extensive task than designing a gain schedule. Figure 1 shows a top level block diagram for the ANDI system.

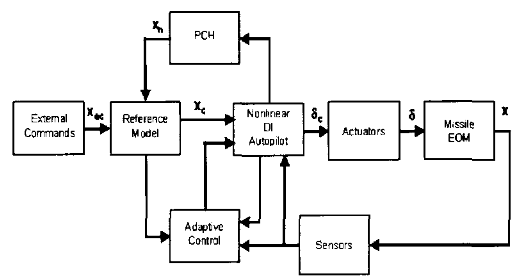

Fig. 1. ANDI Top Level Block Diagram

The "External Commands" models guidance commands. These commands are issued to the "Reference Model" which produces the desired command trajectory. This trajectory is the input to the "Nonlinear DI Autopilot" and the ANN located inside the "Adaptive Control". The ANN augments the DI based on a Lyapunov learning rule in order to achieve the desired trajectory. The "PCH" adjusts the "Reference Model" maintaining the trajectory within system capability. The DI with the ANN produce fin commands for the "Actuators" which produces fin deflections. The equations of motion, "Missile EOM", use the fin deflections to generate body angles, forces, and moments. The "Sensors" observes the changes in the missile state and produces feedback information for the autopilot within the accuracy of the sensors.

A. Dynamic Inversion

DI is a specific type of feedback linearization where the nonlinear plant dynamics are inverted and used as feedback. This technique requires exact knowledge of the plant dynamics. This requirement can be overcome by including an adaptive element to correct for inaccuracies. Typically DI can only be applied to systems that are minimum phase. Tail controlled missiles are non-minimum phase when acceleration at the center of gravity (CG) is used as a system output. This problem is overcome using DI on the autopilot inner loop only, which redefines the output to be minimum phase. [5] [3] [6]

B. Adaptive Neural Network

There are two methods of adaptive control: direct and indirect. The indirect method involves an adaptive system that produces estimates of system parameters. With the direct adaptive method, the algorithm adjusts the control parameters directly, which may not translate to physical system parameters at all. One method of direct adaptive control uses ANNs which are widely used for their ability to accurately approximate continuous nonlinear functions. When used to augment DI, ANNs can help remove the effects of system and aerodynamic modeling inaccuracies. This paper is restricted to multilayer feedforward networks. The weights of the various layers are trained using an online update law, designed using a Lyapunov stability proof. The resultant system modifies the weights continuously and augments the computed control signal. This increases the robustness of the DI autopilot to uncertainties in the inversion parameters. [2] [3]

C. Supporting Technologies

1) Model Following: The reference model provides the ideal closed loop behavior of the system. The reference models used in the ANDI autopilot are second order in observability canonical form. This form for the reference model is specified by the ANN and the EO. As long as the error observer is of the required form then the ANN training laws will work as intended. For a system attempting to follow a step input, large errors are immediately observed by the autopilot. These errors will generate, through feedback signals, large control commands which drive the system to the commanded levels rapidly. When a continuous reference model replaces the step command the initial errors observed by the autopilot are small and grow slowly producing a slow response. Therefore in order to accurately follow a given reference model trajectory, the autopilot must provide lead using feed-forward signals computed from the desired trajectory.

2) Output Redefinition: In order to use DI on non-minimum phase systems, the autopilot is separated into two elements, an inner loop and an outer loop. [3] The inner loop is minimum phase and suitable for DI while the outer loop maintains the non-minimum phase characteristics of the system. To bridge the two elements, the output of the outer loop is redefined in terms of the appropriate minimum phase variables, a combination of α and q in the pitch channel and β and r in the yaw channel.

3) Outer Loop Control: The outer loop control stabilizes system accelerations using classical PI control techniques. ANDI uses PI control on the error signals. The gains for the PI control are calculated using the desired ζ and ω of the outer loop transfer function. The outer loop control also includes a feed forward term based on the commands from the reference model.

4) Error Observer: The weight training laws of each artificial neural network require knowledge of the error between the model state and the missile state. However, only the missile output (acceleration) is available, not the state. Using an error observer driven by the output error, an estimate of the state error is obtained. [2] The error observer model is a LTI system based on the reference model dynamics. In order to match the minimum phase characteristics of the reference model outputs, the plant outputs are converted to minimum phase.

5) Pseudo Control Hedging: A commanded control level may not be fully achieveable due to fin rate or position saturation. The achieved actuator position can be estimated by modeling the response of the actuators to command. The pseudo control hedging signal is the amount of pseudo control lacking due to actuator saturations. [4] In the ANDI model, the command is produced not by the reference model, but from the outer loop acting on the commanded and measured accelerations.

III. Conclusion

This paper has presented an introduction to the ANDI autopilot on a skid-to-turn missile model. The commanded accelerations are processed by a reference model to provide the desired missile behavior. The ANN uses the response from the reference model and the DI autopilot to remove inversion errors and adjust the control signal to the actuators to achieve the desired acceleration response. The outer loop control maintains the non-minimum phase characteristics of the system while the inner loop control generates the minimum phase control signal used by the DI. PCH is used to adjust the reference model response when it would drive the system beyond the physical capabilities of the actuators.

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