Adaptive Control of Highly Uncertain Nonlinear Systems

Final Report

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Contents

1. Objectives

The objectives of this research effort are:

1. Developing novel adaptive control architectures and adaptation laws capable of "learning" poorly modeled behavior in nonlinear systems, particularly the effects associated with unmodeled dynamics and poorly modeled disturbance processes,

2. Extending our existing theoretical framework to adaptively augment observer based linear control designs for linear time-varying systems,

3. Transitioning new research results through collaborative efforts with industry and government laboratories.

The main scientific merit of the proposed research will be twofold: i) establishing a rigorous theoretical framework along with sufficient conditions for stability or boundedness of error signals, ii) seeking transition of these results to problems of high value to the Air Force and aerospace industry through a close collaboration with Boeing Phantom Works, Guided Systems Technologies (GST), a small business closely affiliated with the School of Aerospace Engineering), AFWL, AFRL, and through existing NASA and DARPA funded efforts in place at Georgia Tech.

The AFRL point of contact for all of this research has been Johnny Evers, AFRL/MNGN, Eglin AFB, FL, (850) 882-2961 x2347, collaboration on vision based guidance and control.

2. Accomplishments

2.1 Accomplishments in Year-1

Our main accomplishments in Year-1 were the development of novel adaptive approach that permits augmentation of an Extended Kalman Filter (EKF). This permits extensions to nonlinear and time varying systems, such as are commonly encountered in tracking problems. We also have several experimental efforts underway, including laboratory experimentation on a flexible robotic arm and a formation flight control experiment at Cornell University. Finally, we have worked out several improvements in the manner in which our adaptive control architecture can be applied to output feedback systems that are non-affine in control.

Adaptive State Estimation: Recently, we have examined the problem of augmenting an extended Kalman filter (EKF) with an NN. As a typical problem formulation we treat process dynamics of the form

$$\begin{aligned} \dot{x} &= f(x,z) = f_o(x) + bz_1 \\ \dot{z} &= h(z) \\ y &= c^T x \end{aligned}$$

where $x \in D_x \subset R^{n_x}$, $z \in D_z \subset R^{n_z}$ are the states variables, D_x and D_z are compact sets, and $z_1 \in R$ is an element of z having a known bound. The function $h(z)$ is assumed unknown, except that the relative degree of the measurement $y \in R$ with respect to z_1 is known. A typical application in tracking lies in estimating the position of a target vehicle (the elements of *x*) without having a model for the vehicle's velocity profile, with z_1 being the velocity. In such an application, it is common to use the dynamics of x to design an EKF, with z_1 treated as a random process. Such approaches can easily lead to suboptimal and possibly divergent estimation if the target's behavior isn't random, particularly when the EKF outputs are employed in a guidance law, and the sensor is located on a on a pursuing vehicle.

Our analysis considers augmenting an EKF with an adaptive element. The estimator has the form

$$\dot{\hat{x}} = f_o(\hat{x}) + b\hat{M}^T\sigma(\mu) + K(t)\left(y - \hat{y}\right)$$
$$\hat{y} = c^T\hat{x}$$

where $K(t)$ represents the EKF gain. The augmenting term $\hat{M}^T\sigma(\mu)$ represents the output of a universal approximator (a linearly parameterized neural network) in which the gains are adapted by making use of the residuals produced by the EKF. We have been prove uniform ultimate boundedness of the error process, $e = x - \hat{x}$, and the weight histories by using a back stepping approach. The idea is based on the assumption the EKF provides asymptotic tracking in the absence of target acceleration.

As an illustration consider the situation in which a follower aircraft is regulating its range to a leader aircraft, by feeding back *estimates* of the target velocity. The available measurements are line-of-sight angle and the angle subtended by the target on an image plane. Preliminary results in this line of research are very promising. Figure 1 illustrates the performance of the NN based EKF when compared with the EKF. The goal was to maintain a commanded range of 2 wing spans between the target and the follower, with the target performing a box trajectory maneuver.

<u>*Augmenting Adaptive Output Feedback Control [J4,C3,C6]:*</u> The effort to augment an existing linear controller using an adaptive element led to various experimental tests in real-time environments. In collaboration with the Prof. Wayne Book in the department of Mechanical Engineering at Georgia Tech., the method has been implemented to augment an existing inertial damping mechanism in flexible robotic manipulators in Fig. 2. The objective of the control design is to compensate for the flexibility of the micromanipulator and suppress vibrations. In the test bed, the micromanipulator is mounted at the tip of a cantilevered beam. This resembles a micromanipulator with its joints locked. The inertial damping control combines acceleration feedback with a separately designed position control for the micromanipulator. The dynamics of this under-actuated system features flexibility in hydraulic actuation devices, and a non-minimum phase zero due to non-collocated acceleration sensor and the actuator. With the adaptive element

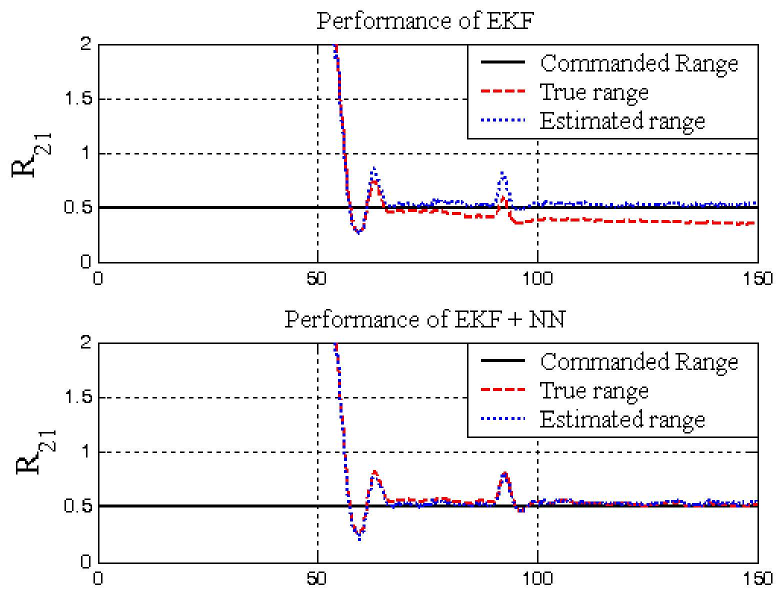


Fig 1: Comparison of Target to Follower Range Estimates.

augmented, fine tip-positioning was achieved with decrease in settling time while vibrations due to flexibility of the cantilevered beam are suppressed to a smaller level. Further, the augmented control system overcomes actuation nonlinearities such dead zone and stiction, and achieves the accuracy on the order of the encoder resolution (0.044^{o}) as shown in Fig. 3. In [C2], an adaptive observer was utilized to tackle an unmatched uncertainty wherein the existing control system is based on a linear observer. In simulation with an inverted pendulum, the adaptive signal was used to compensate for an unmatched uncertainty, and succeeded in regulating the pendulum in the nonlinear region where a linear controller fails to stabilize the system.

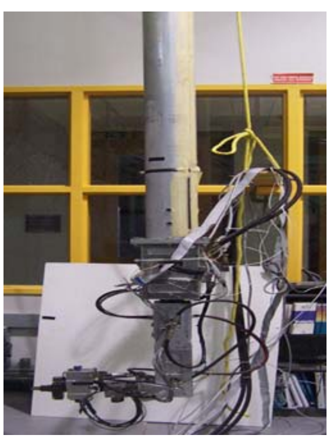


Fig. 2 Testbed at GA Tech.

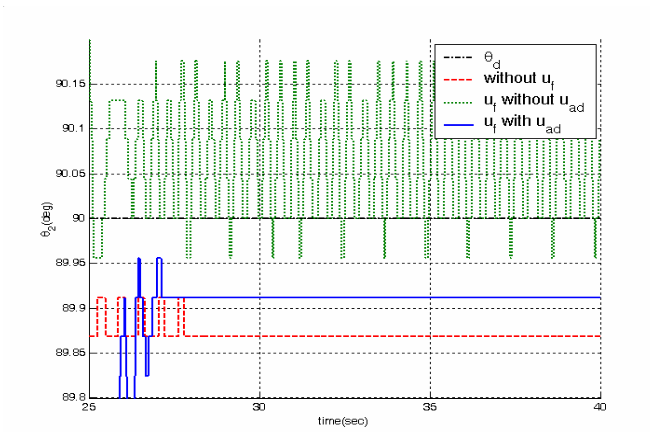
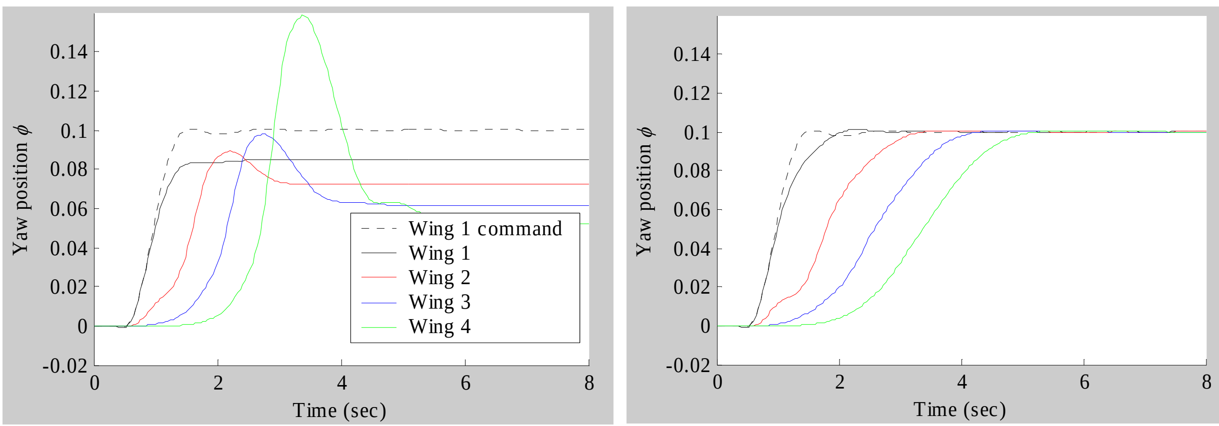


Fig. 3 Joint Angle Responses

Formation Control Experiment at Cornell: Augmenting NN based adaptive controller designs have been tested in simulation on a formation flight problem. In a cooperative work with Prof. Raffaello D'Andrea from the Mechanical and Aerospace Engineering school of Cornell University, linear distributed controllers for a formation of four wings have been augmented with NN based adaptive controllers. It is assumed that every wing in the formation is affected by the existence of the upstream wing. Distributed controllers are interconnected in the same way as the plant, i.e., every controller is influenced by the controller of its upstream wing. It has previously been shown that a distributed controller structure can provide much of the performance of a centralized controller with a much simpler controller structure. However, in the wind tunnel experiment setup, due to unmodeled nonlinearities and disturbances in the system, model based controllers that do not consider these effects do not perform as expected. In simulations, we have shown that augmenting adaptive controllers can successfully eliminate the effects of the nonlinear couplings. Figure 4 provides a sample result from our simulations. Future work will include experimental validation of these designs.



(a) Existing distributed controllers. (b) Augmented controllers.

Fig. 4. Comparison of controllers for the Cornell Wind Tunnel Experiment.

Improvements in Adaptive Laws [C1, C7]: One of the common assumptions in adaptive control is knowledge of the sign of control effectiveness. This issue was addressed in previous work for the case of non-affine systems by introducing a fixed point assumption for the mapping from the adaptive signal to the modeling error, but the knowledge of the sign of the control effectiveness does not appear explicitly in the stability analysis. Furthermore, the contraction mapping assumption may be overly conservative. We eliminated the fixed point assumption in adaptive control of non-affine systems and clarified the role that knowledge of the sign of control effectiveness plays in adaptive control of non-affine systems. Also, an extension from linearly to nonlinearly parameterized neural networks is given for a direct adaptive output feedback approach, and an extension that permits the introduction of e-modification was also developed. This has eliminated a problem a problem with the network weight returning to zero during periods when the commands are constant. Also, conditions under which asymptotic tracking can be achieve were also identified.

2.2 Accomplishments in Year-2

Our main accomplishments in Year-2 have been refinement and stability analysis of a novel adaptive approach that permits adaptive augmentation of an Extended Kalman Filter (EKF) in a feedback control setting. Previously the development in this direction was limited to problems in state estimation. This permits extensions to nonlinear and time varying systems, such as are commonly encountered in guidance problems. We also initiated a new effort aimed at improving exiting adaptation laws with the viewpoint of having the weights converge to their ideal values. We are presently exploring the connections that this work has to requirement for persistency of excitation. Finally we have completed several experimental efforts for which we had only simulation studies in the previous year

Adaptive State Estimation and Control [C1]: We have extended the problem of augmenting an extended Kalman filter (EKF) to address the issue of the combined problem of adaptive estimation and control. In problem formulation, we include a control input in the process. The design of the control law is based on the estimates provided by a neural network (NN)-based adaptive EKF. This approach is developed from the perspective of addressing typical problems such as missile-target tracking and formation flight control. In this approach we treat process dynamics of the form

$$\begin{aligned} \dot{x} &= f(x) + B_1 z_1 + B_2 u, \quad && x(0) = x_0 \\ \dot{z} &= h(z), && z(0) = z_0 \\ y &= Cx \end{aligned}$$

where $x \in D_x \subset R^{n_x}$, $z \in D_z \subset R^{n_z}$ are the states variables, D_x and D_z are compact sets, $f(x): D_x \to R^{n_x}$ is a known smooth function which can be expressed as a Taylor series expansion for all values of x in the domain of interest D_x , $h(z): D_z \to R^{n_z}$ is assumed unknown, $z_1 \in R^{n_{z_1}}$ is a part of the unmodeled dynamics z having a known bound, u is a vector of control inputs and y is the vector of available measurements. The adaptive estimator has the form

$$\begin{aligned} \dot{\hat{x}} &= f(\hat{x}) + B_1 \hat{M}^T \sigma(\mu) + K(t)\big(y - \hat{y}\big), \quad \hat{x}(0) = \hat{x}_0 \\ \hat{y} &= C\hat{x} \end{aligned}$$

where $K(t)$ represents the EKF gain. The augmenting term $\hat{M}^T \sigma(\mu)$ represents the output of a linearly parameterized NN.

Novel Adaptive Control and Estimation Approach: *Novel Approach to Adaptive Control and Estimation:* We have initiated research into a novel adaptive law that uses time histories of system behavior and control input to adjust the weights of a linearly parameterized NN, so that the resulting NN weights belong to a set S^*, which is a neighborhood of the ideal weights whose size is determined by the NN reconstruction error. The set S^* is represented as an intersection of N families of hyperplanes in the space R^N, where N is the number of neurons used to approximate modeling error. A necessary and sufficient condition for the set S^* to be bounded is that the matrix:

$$M = \begin{bmatrix} \int_{t_1}^{T_1} \sigma_1(x(s),u(s))ds & \dots & \int_{t_1}^{T_1} \sigma_N(x(s),u(s))ds \\ \dots & \dots & \dots \\ \int_{t_N}^{T_N} \sigma_1(x(s),u(s))ds & \dots & \int_{t_N}^{T_N} \sigma_N(x(s),u(s))ds \end{bmatrix}$$

is invertible, where x is state-vector, u is control input and σ_i are NN basis functions. Thus, in constructing the matrix M, we seek N time intervals $[t_i, \quad T_i]$, $i = 1, \quad 2, \quad \dots \quad N$ such that vectors $\int_{t_i}^{T_i} \sigma(x(s),u(s))ds$ are linearly independent. The matrix M is obtained by stacking a new vector $\int_{t_i}^{T_i} \sigma(x(s),u(s))ds$ if it is linearly independent of already stacked vectors $\int_{t_n}^{T_n} \sigma(x(s),u(s))ds$, $n = 1, \cdots, i-1$. At the same time, every new vector $\int_{t_i}^{T_i} \sigma(x(s),u(s))ds$ defines a family of parallel hyperplanes S_i in the NN weights space R^N, and the NN weights are driven to the intersection of available families of hyperplanes by the following adaptive law:

$$\dot{\hat{W}}_L = -L_{i\times i}^{-1} E_{c_i} (L_{i\times i} \hat{W}_L - b_i) \text{, and } \dot{\hat{W}}_n = 0 \text{, } n = i+1, \dots, N$$

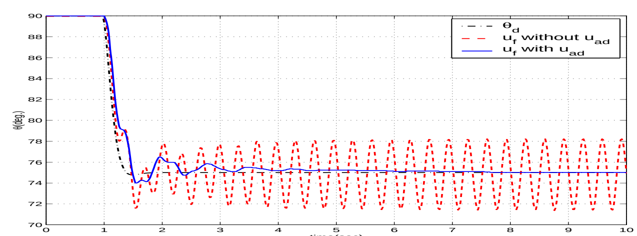
where $\hat{W}_L = \begin{bmatrix} \hat{W}_1 & \hat{W}_2 & \dots & \hat{W}_i \end{bmatrix}^T$, $L_{i\times i}$ is a the nonsingular sub-matrix of M of rank i, $b_i = [F_1(T_1, t_1, x(\cdot), \nu_{ad}(\cdot)) \quad \dots \quad F_1(T_i, t_i, x(\cdot), \nu_{ad}(\cdot))]^T$, $E_{c_i} > 0$ is the adaptation gain, $F_1(T_i, t_i, x(\cdot), \nu_{ad}(\cdot)) = x(T_i) - x(t_i) - \int_{t_i}^{T_i} Ax(s)ds + \int_{t_i}^{T_i} B\nu_{ad}(s)ds$. That is, only those NN weights corresponding to the nonsingular part of the stacked matrix M are updated while the remaining NN weights are frozen. After N independent vectors $\int_{t_i}^{T_i} \sigma(x(s),u(s))ds$ are obtained, all the NN weights are updated and are guaranteed to converge exponentially to a point inside the set $S^* = \bigcap_{i=1,\cdots N} S_i$. This is in contrast to the current adaptive law:

$$\dot{\hat{W}} = -E_{c_N} \sigma(x,u) e^T PB$$

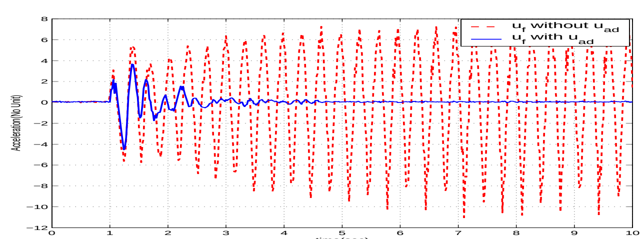
where e is the tracking/regulation error, P is the solution of Lyapunov equation: $A^T P + PA = -Q$, for some $Q > 0$. Notice that the current adaptive law, derived from Lyapunov-like stability analysis, updates all the NN weights simultaneously in an attempt to decrease the error e, without regard to having $\hat{W}$ approach an ideal value, while the new approach tries to decrease the error by driving the NN weights close to their ideal weights. In this new scheme, control and estimation are simultaneously performed. Simulation studies thus far with a first order system shows that this approach is very effective when the number of neurons is not too large. Currently, simulations with the new adaptive law for more complex systems are under way. At the same time a connection between existence of the invertible matrix M and the persistency of excitation condition in the adaptive control literature is also being investigated. This approach may be able to relax the requirement of knowing the sign of the control effectiveness. As of yet none of this research has been published.

Augmenting Adaptive Output Feedback Control [J2,C2,C4]: The continuing effort to augment existing linear controllers using an adaptive element led to a successful experimental test in a real-time environment. In collaboration with the Prof. Wayne Book in the department of Mechanical Engineering at Georgia Tech., the method has been implemented to augment an existing inertial damping mechanism in the flexible robotic manipulator in Fig. 1. The objective of the control design is to compensate for the flexibility of the micromanipulator and suppress vibrations. In the test bed, the micromanipulator is mounted at the tip of a cantilevered beam. This resembles a micromanipulator with its joints locked. The inertial damping control combines acceleration feedback with a separately designed position control for the micromanipulator. The dynamics of this under-actuated system features flexibility in hydraulic actuation devices, and a non-minimum phase zero due to non-collocation of the acceleration sensor and the actuator. The potential benefits of the augmenting adaptive controller in terms of robustness are illustrated in Fig. 2, in which lead weights of approximately 10.56 Kg are mounted on the wrist. This inertia change simulates the situation when the manipulator picks up a massive object. Without augmenting adaptive elements (red dotted line in Fig. 4), the existing system immediately goes unstable while the augmented control system (blue solid line in Fig. 4) quickly stabilizes the unstable system and maintains good performance in both the joint angle regulation and vibration suppression. An added benefit of adaptive augmentation is fine tip-positioning. Accuracy on the order of the encoder resolution was achieved by overcoming nonlinear actuation effects such as dead zone and stiction.

Figure. 1 Testbed at GA Tech.



(a) Joint angle response

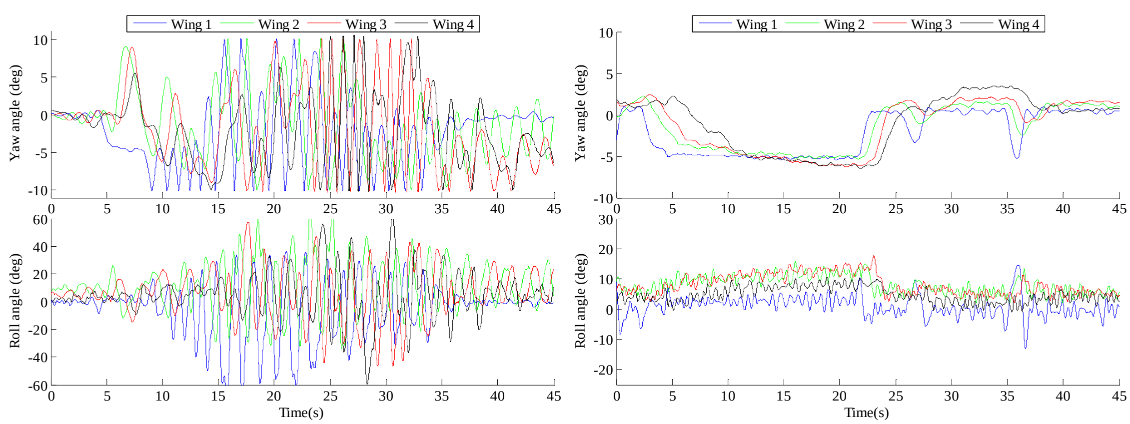


(b) Base acceleration response

Figure. 2 Experimental results with the increased mass.

Theoretical Clarification on Adaptive Laws [C3, C6]: One of the common assumptions in adaptive control is knowledge of the sign of control effectiveness. This issue was addressed in previous work for the case of non-affine systems by introducing a fixed point assumption for the mapping from the adaptive signal to the modeling error, but the knowledge of the sign of the control effectiveness does not appear explicitly in the stability analysis. Furthermore, the contraction mapping assumption may be overly conservative. We eliminated the fixed point assumption in adaptive control of non-affine systems and clarified the role that knowledge of the sign of control effectiveness plays in adaptive control of non-affine systems in [C3] using the mean value theorem. However, the result was obtained by introducing an assumption on the boundedness of the time derivative of the control effectiveness. This assumption has been relaxed, and many theoretical issues regarding non-affine systems are further clarified in [C6].

Formation Control Experiment at Cornell [C7]: Augmenting NN based adaptive controller designs previously tested in simulation on a formation flight problem have been verified on Cornell wind tunnel experiment setup. In a cooperative work with Prof. Raffaello D'Andrea from the Mechanical and Aerospace Engineering school of Cornell University, linear distributed controllers for a formation of four wings have been augmented with NN-based adaptive controllers. It is assumed that every wing in the formation is affected by the existence of the upstream wing. Distributed controllers are interconnected in the same way as the plant, i.e., every controller is influenced by the controller of its upstream wing. It has previously been shown that a distributed controller structure can provide much of the performance of a centralized controller with a much simpler controller structure. However, in the wind tunnel experiment setup, due to unmodeled nonlinearities and disturbances in the system, model based controllers that do not consider these effects do not perform as expected. In the experiment setup, four wings are mounted in a half-vee formation and each wing moves independently with two degrees-of-freedom, roll and sway (lateral motion), which is implemented as yaw about an axis some distance behind the wing. The goal is to maintain synchronous motion of the formation in which the leader wing is given an external yaw command and each downstream wing is to maintain a relative position with respect to the nearest upstream aircraft to minimize the total induced drag. Due to the fact that lateral motion is implemented as yaw, local dynamics of wings change when a nonzero command is given. For yaw commands as little as 5 deg, these changes come to a point where the linear controller tuned for zero yaw can no longer tolerate the ambient noise in the tunnel. Fig. 3 provides a sample result from the wind tunnel experiments when a yaw command of –5 deg is given to the leader wing, which is more than half of the available yaw motion. Formation quickly gets unstable with the existing distributed controllers as shown in Fig. 3 (a). Fig. 3 (b) shows that stability is maintained with the augmented controllers.



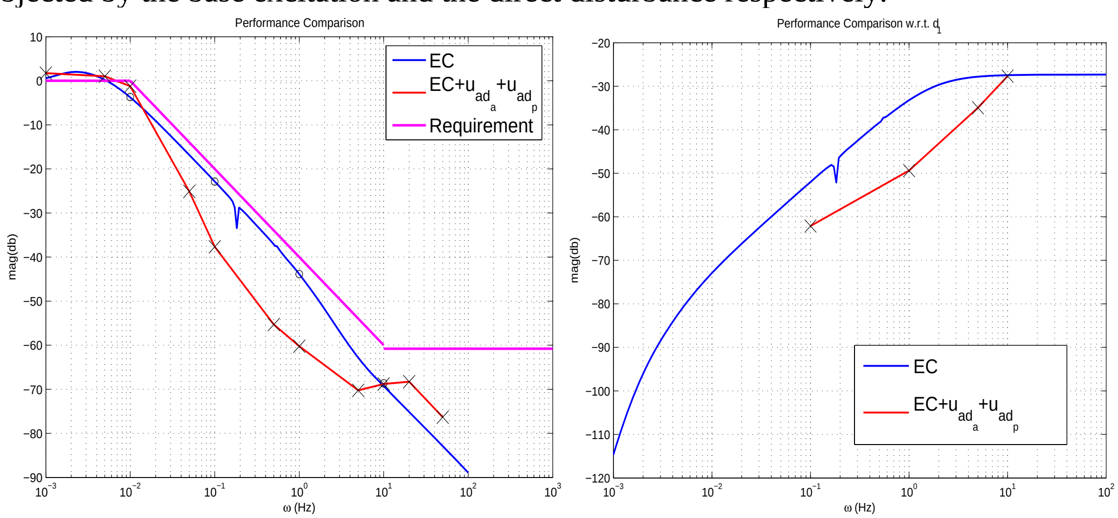
(a) Existing distributed controllers. (b) Augmented controllers.

Figure. 3. Comparison of controllers for the Cornell Wind Tunnel Experiment.

2.3 Accomplishments in Year-3

Our main theoretical accomplishments in Year-3 have been to focus on improvements in methods of adaptation, with particular emphasis on application problems in which we have found deficiencies when employing standard adaptive approaches. These include adaptive methods for non-affine, non-minimum phase systems, a novel composite adaptive approach to estimation, and a new composite-like adaptive approach we call q-modification. We have also used some of our funding to support application of previously developed methods to adaptive control of flexible systems.

Adaptive Output Feedback Control for Flexible Systems [J2,J3,J4,C1,C4]: A methodology in [J2] that augments existing linear (and nonlinear) controllers using an adaptive element have been applied to control of flexible systems. Previous efforts to control a laboratory torsional system and a flexible base robot manipulator have also been submitted for journal publications [J3,J4]. In [C1], we applied the methodology for a simplified microgravity isolation system deduced from the space science vibration isolation system, g-LIMIT (gLovebox Integrated Microgravity Isolation Technology), developed and tested by NASA Marshall Space Flight Center. An existing control system employs a classical controller that combines a high-gain acceleration inner-loop feedback together with a low-gain position outer-loop feedback to regulate the platform about its center position. The control design considers both parametric and dynamic uncertainties because the isolation system must accommodate a variety of payloads having different inertial and dynamic characteristics. An important aspect of the control system is the accelerometer bias and the deviation of the platform it causes as a result of integral control. By employing adaptive neural networks for both the inner-loop and outer-loop controllers, we illustrate that adaptive control can improve both steady-state responses and transient responses in position. A feature in the design is that high-band pass and low pass filters are applied to the error signal used to adapt the weights in the neural network and the adaptive signals, so that the adaptive processes operate over targeted ranges of frequency. This prevents the inner and outer loop adaptive processes from interfering with each other. Figure 1 illustrates the improvement obtained by the adaptive controller when the system is subjected by the base excitation and the direct disturbance respectively.

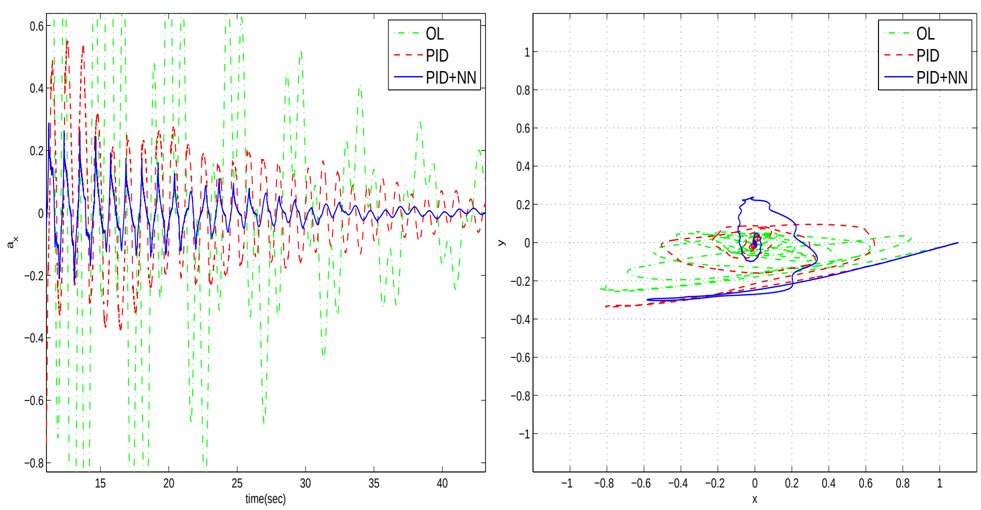


(a) Isolation Performance with Base Excitation.

(b) Isolation Performance with Direct Force.

Fig. 1. Performance of Vibration Isolation

We also initiated an effort to control a large flexible solar sail that has been suggested as a propulsion system that enables future deep space missions [C4]. Solar sail technology is being developed by the In-Space Propulsion Technologies Program, managed by NASA's Office of Space Science and implemented by the In-Space Propulsion Technology Projects Office at Marshall. In order to compensate for inherent flexibility due to its large size and lightweight, an initial step is to evaluate the available control methodologies using SAFE (Solar Array Flight Experiment) boom, which had been carried by Space shuttle and then has been set up for control structure interaction at NASA Marshall. Figure 2 shows preliminary simulation results for the boom model in which X and Y directional motions are coupled. Conventionally, coupling effects are difficult to model and therefore are ignored in most structural control problems. As a result, a proportional-integral-derivative (PID) controller, designed in a decoupled manner, damps the mechanical energy imposed by initial movements in only X direction in a way proportional to the initial condition. In contrast, an adaptive controller distributes this mechanical energy equally to X-Y direction due to neural network (Both neural networks compete each other to suppress the vibrations in their own direction). Overall, the adaptive controller damps out the vibration faster than the PID controller.



(a) Acceleration Response in X-direction

(b) Tip Displacement in X-Y plane

Fig. 2. Time Responses of the acceleration and the displacement of the boom tip

<u>Theoretical Research on Non-affine Non-minimum Phase Systems[J5,C2,C3,C5]:</u> One of the common assumptions in adaptive control is knowledge of the sign of control effectiveness. This issue was addressed in previous work for the case of non-affine systems by introducing a fixed point assumption for the mapping from the adaptive signal to the modeling error, but the knowledge of the sign of the control effectiveness does not appear explicitly in the stability analysis. Furthermore, the contraction mapping assumption may be overly conservative. We eliminated the fixed point assumption in adaptive control of non-affine systems and clarified the role that knowledge of the sign of control effectiveness

plays in adaptive control of non-affine systems using the mean value theorem. However, the result was obtained by introducing an assumption on the boundedness of the time derivative of the control effectiveness. We relaxed this assumption and clarified many theoretical issues regarding non-affine systems in [J5,C2]. Based on this theoretical foundation for control of non-affine systems, a backstepping-based adaptive control method has been developed to stabilize the following non-affine non-minimum phase systems having the form

$$
\begin{aligned}
\dot{\eta} &= f_o(\eta,\bar{\xi}_{l-1}) + g_o(\eta,\bar{\xi}_{l-1})\xi_l + \Delta\eta(\eta,\bar{\xi}_{l-1}) \\
\dot{\xi}_i &= \xi_{i+1},\ \ i = 1,\cdots,l-2, \\
\dot{\xi}_{l-1} &= \xi_l, \\
&\ \ \vdots \\
\dot{\xi}_r &= h(\eta,\xi,u), \\
y &= \xi_1
\end{aligned}
$$

where $\bar{\xi}_{l-1} = [\xi_1,\cdots,\xi_{l-1}]^T \in R^{l-1}$, $\xi = [\bar{\xi}_{l-1}{}^T,\xi_l,\cdots,\xi_r]^T \in \Omega_\xi \subset R^r$, $\eta \in \Omega_\eta \subset R^{n-r}$ are the state variables, u is the input, and y is the output, $h(\eta,\xi,u)$ is the control effectiveness term in which u appears in a non-affine manner. In [C3], we first seek a state ξ_l, $1 \le l \le r$, which can stabilize the internal dynamics and then perform backstepping. An immediate consequence is that the backstepping approach can be applied to more general class of systems compared to the class in the literature because additional states, $\xi_1 \cdots \xi_{l-1}$, can appear in the internal dynamics. An additional benefit is that it lessens the complexity of backstepping controller, which increases dramatically when the plant relative degree is high. By starting backstepping at ξ_l, only $r-l+1$ backsteps are required before the control appears. At the final step of backstepping, a control law is derived by *statically* inverting an invertible function and compensating for inexact inversion by augmenting a neural network as is done in [J5]. In [C5], a tuning function is introduced to reduce the number of neural networks that are employed at each stage of backstepping in the literature.

<u>*Adaptive State Estimation [C6,C8]*</u> : We have developed a modification of our approach for augmenting an Extended Kalman Filter (EKF) with an adaptive neural network (NN) for state estimation of uncertain nonlinear systems in the presence of unmodeled dynamics [C6]. The application is to the problem of maneuvering target tracking wherein the target maneuvers represent the unmodeled dynamics in the problem formulation. In the previous approach [C6], the NN is trained online using the residuals of the EKF. The objective in the design is to estimate the unknown target maneuvers in real-time and compensate the EKF. However, in a particular application of this approach, we found it difficult to identify a fixed set of NN design parameters that could give reasonable target acceleration estimates for varying target maneuvers. This in turn gave rise to state estimation errors that were larger than expected. One possible explanation is that the residuals of the EKF used to train the NN online do not contain sufficient information.

We developed a modification to the previous approach by deriving an additional error signal to train the NN. We assume that the target acceleration is linearly parameterized in terms of an ideal set of NN weights. We then derive a linear parameterization model in terms of available system signals and the ideal, but unknown, NN weights. Replacing the ideal NN weights with their estimates in the linear parameterization model provides an estimate of the "system output". The difference between the "system output" and its estimate is the additional error signal that is utilized to train the NN. This approach of using additional error signals to improve the performance of the NN is referred to as a composite adaptation approach to adaptive state estimation [C2].

The benefits of using an additional error signal to train the NN are clearly evident in the simulation results. The results show that the target acceleration can be estimated to a reasonably accurate degree and the state estimation errors are much smaller when compared to the case when there is no adaptation (nominal case, simple Kalman filter with white noise modeling of the target acceleration) and the case when the adaptive law in [C6] is applied. Most important is the fact that the performance does not change significantly over varying target maneuvers. When compared to [C6], the modified approach [C8] is limited thus far to state estimation of systems whose nominal model is linear and time-invariant. Figure 1 shows the azimuth rate estimation performance with the approach in [C6] for a target executing a circular trajectory maneuver. Figure 2 shows the corresponding plot with the composite adaptation approach [C8]. In the figures the red solid lines in the upper sub-plots represent the true azimuth-rate time history and the blue dotted lines represent the estimate. The bottom sub-plots show the estimation error in deg/s. The results show that the estimation errors with the composite adaptation approach [C8] are significantly smaller than with the previous approach in [C6]. Figures 3 and 4 show the azimuth rate estimation performance for a target executing a square-box trajectory maneuver. The results show that the composite adaptation approach [C8] gives consistently better results than the previous approach in [C6].

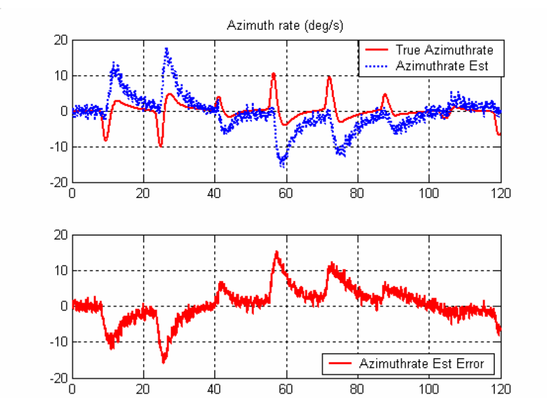


Figure 1. Azimuth rate estimation [C1] for a circular trajectory target maneuver

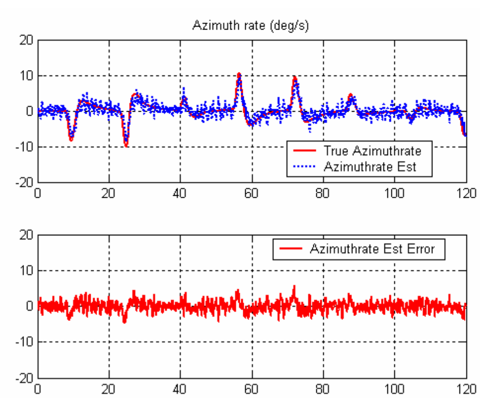


Figure 2. Azimuth rate estimation [C2] for a circular trajectory target maneuver

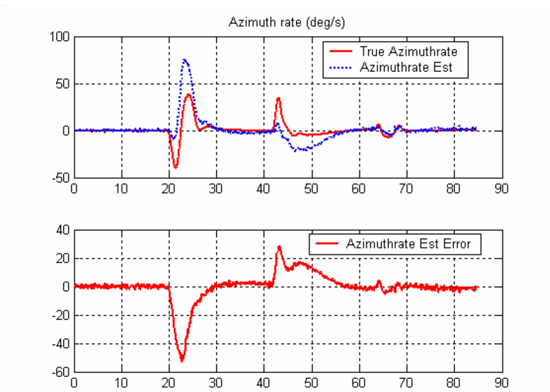


Figure 3. Azimuth rate estimation [C1] for a square-box trajectory target maneuver

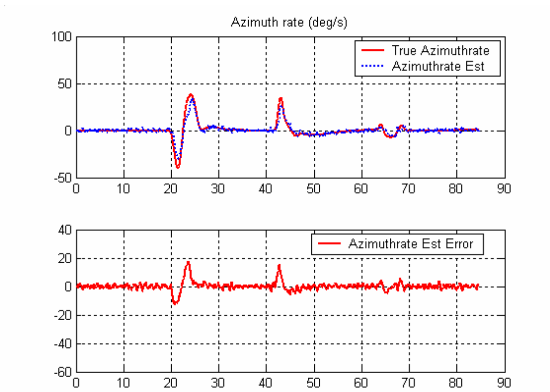


Figure 4. Azimuth rate estimation [C2] for a square-box trajectory target maneuver

Novel Approach to Adaptive Control and Estimation: q-modification [C9,C10]

In the effort to improve the existing adaptive law a new method called q-modification has been developed which uses time histories of system behavior and control input. The design has been accomplished for the case when uncertainty is approximated using linearly parameterized NN. The developed approach is motivated by the observation that the weights in any linearly parameterized representation of uncertainty satisfy an integral equation involving the state and control variables. This equation forms the basis for the development of a novel modification term that offers a possibility of improved rate of adaptation. Stability analysis shows that q-modification adds non-negative term in the derivative of Lyapunov function. It has been shown that with q-modification under certain conditions the weights estimates converge to their ideal values. Although in practice such conditions are not always satisfied and weights estimates do not necessarily converge to the ideal weights, q-modification significantly improves the error tracking. Q-modification appears to be conceptually similar both to composite adaptation. The results of this research have been published in [C9, C10].

3. Transitions

Intelligent Flight Control System Design for the F15: The goal of this effort is to design and evaluate a Neural Network (NN) based adaptive control algorithm for NASA's F-15 aircraft. Prof. Calise developed the flight control software, and provided on-site flight test support. Ultimately this research will be transitioned to a C-17 aircraft.

Government Customers: NASA Ames/Dryden Flight Research Center

Technical POC: Mr. John Burken, (661) 276-3726, john.burken@dfrc.nasa.gov

Formation Flight Control [C7]: New flight control design approach was developed for multi UAV formations aimed at extending range and

endurance. The solution relies on adaptive control and online extremum command generation. The developed methodology mimics piloting techniques during a closed coupled formation flight.

Government Customer: NASA Dryden Flight Research Center
Technical POC: John Burken, 661-276-3726, john.burken@dfrc.nasa.gov
Corporate Customer: Boeing
Technical POCs: Dr. Eugene Lavretsky, (714) 235-7736, eugene.lavretsky@boeing.com

Adaptive Control of Advanced Fighter Aircraft in High α Flight Regimes: The goal of this effort is to demonstrate the use of dynamic inversion based adaptive output feedback control for high angle of attack flight control. The approach is being applied to an F-15 ACTIVE model with thrust-vectoring capability. The model is valid up to 60° angle-of-attack and includes Thrust Vector Control (TVC). The main objective of the control design is to demonstrate adaptation to aerodynamic uncertainty in the form of both unmodeled parameter variations and unmodeled dynamics not present in the nominal inversion design.

Government Customer: NASA Langley Research Center
Technical POC: Mark Motter, (757) 864-6978, m.a.motter@larc.nasa.gov

Adaptive Guidance and Control of Guided Parafoils: Prof. Calise developed an adaptive guidance algorithm and an adaptive autopilot design for the Onyx system of guided parasails that implement NN based adaptive methods developed under AFOSR sponsorship. These algorithms underwent flight testing, including cooperative flight control for a swarm of parasails

Corporate Customer: Atair Aerospace
Technical POC: Dan Preston, President of Atair Aerospace, dan@extremefly.com, 718-923-1709, www.atairaerospace.com.

4. Interactions

Prof. Calise worked in collaboration with Prof. Raffaello D'Andrea from the Mechanical and Aerospace Engineering school of Cornell University on adaptive formation flight control, with the goal of performing wind tunnel experiments in the near future. He also collaborated with Prof. Wayne Book in Mechanical Engineering at Georgia Tech., performing adaptive control experiments on a flexible robotic arm. He also initiated a collaborative effort with Prof. Jason Speyer at in Mechanical and Aerospace Engineering at UCLA in the area of adaptive flow control. Prof. Calise has also maintained an ongoing collaboration with Johnny Evers of AFRL/MNGN in numerous areas related to adaptive guidance and adaptive flight control

5. Patents and Invention Disclosures

Patents

Calise, A.J., Kim, Byoung-Soo, and Corban,J.E., “System and Method for Adaptive Control of Uncertain Nonlinear Processes,” US 6,757,570, June 29, 2004.

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Madyastha, V.K., Calise, A.J., “Adaptive Augmentation of an Extended Kalman Filter for Purposes of Feedback Control,” Invention Disclosure Filed Nov. 2005.

6. Publications

Year-1 Publications: {J-journal, B-book, C-conference}

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[J2] N. Hovakimyan, E. Lavretsky, B.-J. Yang, A. Calise, Coordinated Decentralized Adaptive Output Feedback For Control of Interconnected Systems, *Accepted to* IEEE Transactions on Neural Networks, 2004.
[J3] Calise, A. J., Yang, B.-J., and Craig, J. I., "Augmenting Adaptive Approach to Control of Flexible Systems," ” Journal of Guidance, Control and Dynamics, Vol.27, No.3, pp. 387-396, 2004.
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[C4] Hovakimyan, N., Lavretsky, E., Yang, B-J. Calise, A.J., “Coordinated Decentralized Adaptive Output Feedback Control of Interconnected Systems,” American Control Conference, June 2004.
[C5] Yang, B-J., Calise, A.J., Hovakimyan, N., “Augmenting Adaptive Output Feedback Control of Uncertain Nonlinear Systems with Actuator Nonlinearities, American Control Conference, June 2004.
[C6] Kim, N., Calise, A.J., Hovakimyan, N., “Several Extensions in Methods for Adaptive Output Feedback Control”, American Control Conference, June 2004.
[C7] E. Lavretsky, N. Hovakimyan, A. Calise, V. Stepanyan, Vortex Seeking Formation Flight Neurocontrol, Conference on Guidance, Navigation and Control, 2003.

<u>Year-2 Publications:</u> {J-journal, C-conference}

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[C3] Kim, N., Calise, A.J., Hovakimyan, N., “Several Extensions in Methods for Adaptive Output Feedback Control”, American Control Conference, June 2004.
[C4] Yang, B-J., Calise, A.J., Craig, J.I., “Adaptive Output Feedback Control of a Flexible Base Manipulator,” AIAA Conference on Guidance, Navigation and Control, Aug., 2004.
[C5] Madyastha, V.K., Calise, A.J., “An Adaptive Filtering Approach to Target Tracking”, American Control Conference, June 2005.
[C6] Yang, B.-J, Calise, A.J., “Adaptive Control of a Class of Non-Affine Systems using Neural Networks”, Joint Conference on Decision and Control/ European Control Conference, Dec., 2005.
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[C3] Yang, B-J., Calise, A.J., “Adaptive Stabilization for a Class of Non-Affine Non-minimum Phase Systems using Neural Networks,” American Control Conference, June, 2006.
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[C5] Yang, B-J., Calise, A.J., “Adaptive Regulation for a Class of Non-Affine System using Neural Network Backstepping with Tuning Functions,” to appear in Conference on Decision and Control, Dec., 2006.
[C6] Madyastha, V.K., Calise, A.J., “An Adaptive Filtering Approach to Target Tracking”, American Control Conference, June 2005.
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