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To improve the computational design procedure, and to prepare for studies on BCU arrays, it is necessary to avoid the long computation times that would be required for tracking the response to reaal actuator signals by DNS. Since the control units exploit the (linear) wave superposition for wave attenuation, we have developed a highly efficient simulation technique by combining the results of a single DNS run with the Duhamel superposition integral (DSI). We perform the single run for a small ramp motion of a given actuator and record the flow response at sensor locations. From this time series, DSI generates the flow response to arbitrary actuator motion in milliseconds. The flow response to sample signals agrees perfectly with DNS results for these signals. Figure 5 shows a time series for an actuator that performs a ramp motion in the streamwise direction over about 1% of the TS period and remains deflected at the maximum amplitude of 0.02 mm. the flow response is recorded at a hotwire located one TS wavelength downstream of the actuator and 1/4th boundary layer thickness from the wall. The duration of the signal clearly indicates that instantaneous sensor signals contain contributions from actuator signals over some period of time. Accounting for the actuation history is key to successful feedback control.

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# Flow Control Using Neural Networks

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# Objectives

Drag reduction on aerodynamic surfaces through flow control has economic and environmental benefits. The necessary delay of transition is usually achieved by modifying the highly energetic mean flow over these surfaces by suction to be less susceptible to instabilities. In this case, the net benefits may be reduced by high power requirements, weight, complexity, and maintenance of the suction system. The open-loop control is difficult to optimize and adapt to varying flight conditions. We aim at controlling transition in boundary layers by suppression of the initially weak disturbances in the unstable mean flow using a "smart wall" for active flow control. This active surface consists of an array of basic control units (BCU's). Each BCU combines micro-manufactured sensors and actuators, neural networks, and circuitry for training algorithms embedded in a single layer of silicon. Our first goal is the development of a single BCU to demonstrate the capability of neural networks to "learn" the proper response to disturbances in the flow, and to send suitable signals to an actuator that suppress the disturbances and the evolution toward transition under varying flow conditions. In the second phase, BCU's will be arranged in arrays to control transition over a large surface area. The development of BCU's and BCU arrays rest heavily on computer simulations. Successful models are tested in a low-speed wind tunnel. Feasibility of the hardware implementation of the smart wall is one of the guiding principles of this work.

# Previous Results

## Pretrained Neural Networks

Neural network architectures and training algorithms were analyzed to establish the basis for the controller. Controllers were trained in computer simulations using combinations of artificial instability waves as input. The controllers successfully canceled incoming waves leaving a residual of only a few percent of the original amplitude. When an experimental time series with wave packets recorded in a wind tunnel was used as input, the wave packets were reduced to the noise level. This generalization capability is achieved by proper layout of the neural network.

For wind-tunnel tests in a flat-plate boundary layer, the neural network controller was simulated on a special PC board with signal processing capability. The experimental setup is shown in Figure 1. The microphones are used in pairs to eliminate common noise. A continuous wave train was produced by an upstream disturbance generator. The signals from sensors 1 – 3 were first used to train the controller. After the training completed, the controller successfully cancelled incoming TS waves as witnessed by the change from a turbulent to a laminar signal at the hot wire (at $Re = 1.7 \times 10^6$).

Artificial wave packets produced by the disturbance generator were cancelled using the network trained for the previous case. The controller worked surprising well and laminar flow was recovered at the hot-wire position.

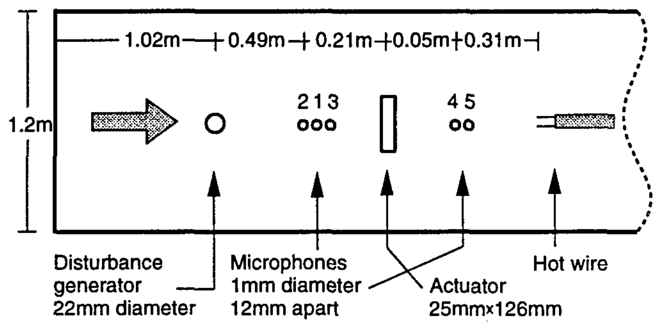


Figure 1: Experimental setup

## Optimization of the BCU

The wind-tunnel tests suggested to account for noise in the design of the BCU. Changes in the training algorithms (use of back-propagation) increased the training speed and lowered the residuals. An optimization of the distances between the microphone sensors and actuator and attention to the noise cancellation resulted in significantly improved input signals to the neural network and a lower signal-to-noise ratio. As a result, no filtering of the signals was required and much better control was achieved. The comparison of results before and after these improvements is shown in Figure 2.

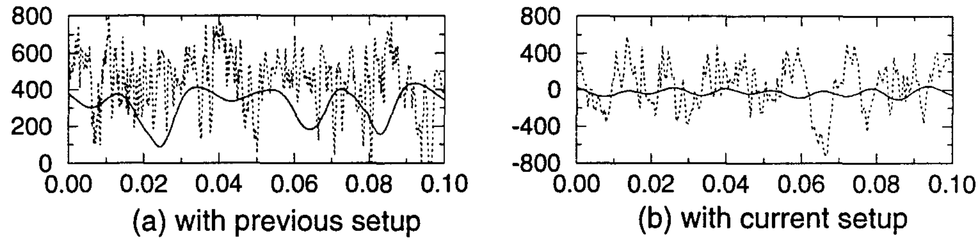


Figure 2: Improvement of network control with new arrangement

## Inverse Control Model

To implement feedback control, it is necessary to obtain a feedback signal (from the downstream pair of microphones) and to model the flow response to actuator motion. An inverse control model appears attractive, because it consists of two identical neural networks. One of these networks is trained to model the system inverse, i.e. the input to the network is the system response from the feedback sensor and the desired network output is the actuator signal that produced this response. The most significant advantage of this inverse model controller is that it does not require the explicit specification of the desired counter-disturbance wave for the network training. The training data are simply real-time measurements of action/response pairs. This enables training the inverse model on-the-fly using the most recent history of action/response pairs. The updated weights are periodically copied to the controller which generates the control signal to drive the actuator. As the inverse model is being trained, a reduced residual level at the controller input would yield a control signal which can actually bring the system response close to the desired zero residual.

Figure 3 shows the convergence history of a typical run of on-the-fly training of the inverse model for wave cancellation. After an initial training period of about 100 TS cycles, almost complete cancellation occurs as a result of wave superposition. The low residual can be maintained if the flow conditions change on a time scale larger than the initial training period.

While the inverse model works well in computer simulations, performance and robustness deteriorate in the wind tunnel. To overcome this problem, steps were taken to develop an alternative (forward) system model and to validate the computational design procedures in more detail.

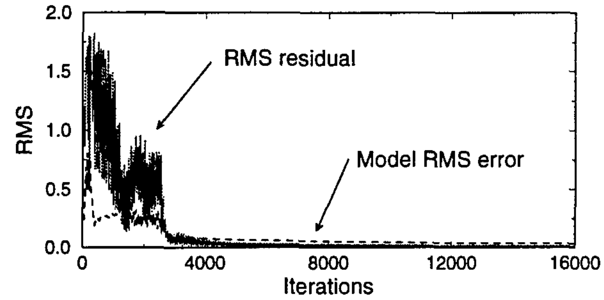


Figure 3: Convergence history of on-the-fly training of inverse model

## Flow Simulation by DNS

DNS studies of the experimental setup were performed to analyze the flow response to actuator movement and to compare with experimental data. Two important results from these studies are the upstream influence of the actuator, as shown in Figure 4, and the relatively short distance of about one TS wavelength over which the actuator excitation has resulted in an almost perfect TS wave. The DNS results are in good agreement with the experiments.

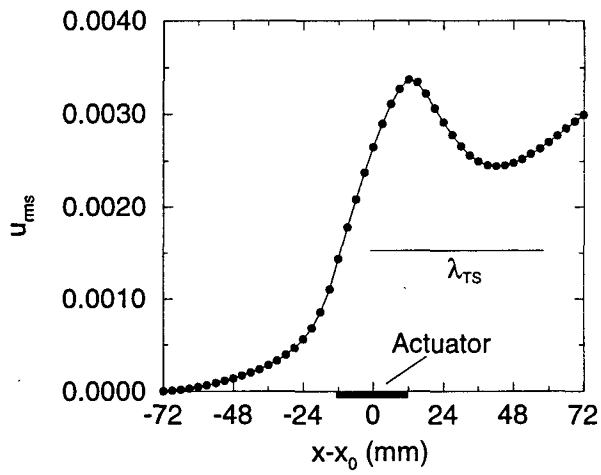


Figure 4: Distribution of $u_{rms}$ along the centerline for sinusoidal actuation at 73 Hz with an amplitude of 0.02 mm. The horizontal line shows the TS wavelength.

# Recent Results

## Computational Design Procedure

To improve the computational design procedure, and to prepare for studies on BCU arrays, it is necessary to avoid the long computation times that would be required for tracking the response to real actuator signals by DNS. Since the control units exploit the (linear) wave superposition for wave attenuation, we have developed a highly efficient simulation technique by combining the results of a single DNS run with the Duhamel superposition integral (DSI). We perform the single run for a small ramp motion of a given actuator and record the flow response at sensor locations. From this time series, DSI generates the flow response to arbitrary actuator motion in milliseconds. The flow response to sample signals agrees perfectly with DNS results for these signals. Figure 5 shows a time series for an actuator that performs a ramp motion in the streamwise direction over about 1% of the TS period and remains deflected at the maximum amplitude of 0.02 mm. The flow response is recorded at a hotwire located one TS wavelength downstream of the actuator and 1/4th boundary layer thickness from the wall. The duration of the signal clearly indicates that instantaneous sensor signals contain contributions from actuator signals over some period of time. Accounting for the actuation history is key to successful feedback control.

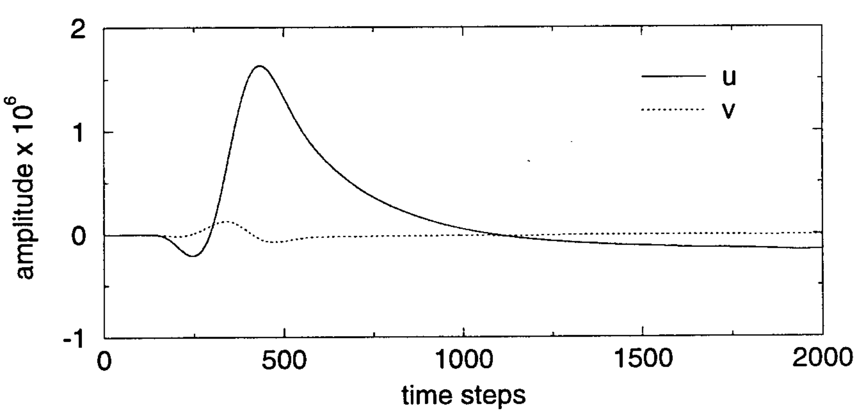


Figure 5: Flow response to ramped actuator motion

## Feedback Control with Forward System Modeling

As an alternative to the earlier inverse system model, a forward system model was developed based on broader experience. In this approach, the network input consists of controller input and output over some time, and the training goal is to match the flow response directly. Using delayed signals, a single upstream sensor produces the controller input. The feedback signal is utilized to derive the model error for the training of the forward system model as well as the control error as the deviation from the desired flow response. The control error is back-propagated through the forward system model to train the controller. The rather complicated training algorithm converges slower for wave packets than for continuous waves to reach small control errors. Through on-the-fly training, the controller adapts to changing flow conditions and disturbances without loss of control. Control is regained within a short time after abrupt changes in conditions.

The controller developed and tested computationally was straightforward ported to the wind tunnel. The controller cancelled continuous waves under changing conditions with great success and quickly adapted to rapid changes. For wave packets, the capabilities of the PC board imposed some limitations that resulted in larger control errors. Nevertheless, the controller reduced the wave packets sufficiently to restore laminar flow at the hotwire position.

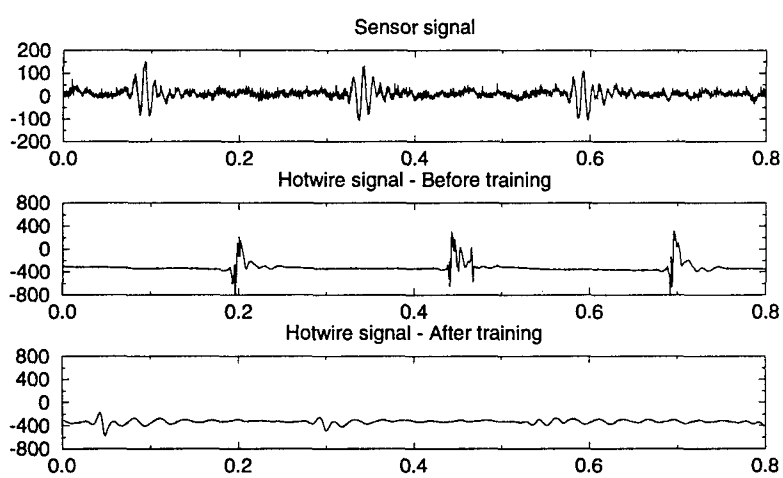


Figure 6: Feedback control of wave packets: before and after training

# Personnel

The following personnel has participated in the work and has been partially supported under this contract:

Thorwald Herbert, Principal Investigator

Joseph H. Haritonidis, Co-Principal Investigator

Xuetong Fan, Ph.D. Student

Lorenz Hofmann, Ph.D. Student

Robert A. Briggs, M.S. Student

Eugene Kalinin, M.S. Student

Lorenz Hofmann has earlier cooperated in this program under an AFOSR-AASERT Fellowship. Xuetong Fan has worked on the design, computer simulation, and wind-tunnel implementation of the control unit. Lorenz Hofmann is responsible for DNS and DSI, and prepares simulations of BCU arrays. Robert A. Briggs has investigated the effect of grid stretching on the multigrid method used for DNS. Eugene Kalinin cooperates in the analysis and physical interpretation of solutions to the adjoint linearized Navier-Stokes equations as a design tool for flow-control systems.

# Degrees

"Laminar Flow Control Models with Neural Networks," by Xuetong Fan, Ph.D. Thesis, The Ohio State University, Columbus, Ohio, December 1995.

"Applications of Multigrid Methods on Stretched Grids," by Robert A. Briggs, M.S. Thesis, The Ohio State University, Columbus, Ohio, October 1995.

# Publications

The following publications were completed or originated from work under support by this contract:

"The Status of Applied Transition Analysis." by Th. Herbert, Proc. Colloquium *Transitional Boundary Layers in Aeronautics; State of the Art and Future Directions of Research*, Amsterdam, Netherlands, December 6-8, 1995. Elsevier, to appear.

"Crossflow-Dominated Transition in Flight Tests," by Th. Herbert and G. Schrauf, AIAA Paper No. 96-0185 (1996). Submitted to *AIAA Journal.*

"Laminar Flow Control with Neural Networks," by Th. Herbert, X. Fan, and J. H. Haritonidis, Proc. ASME 1996 IMEC & E.

"Parabolized Stability Equations," by Th. Herbert, *Annual Review of Fluid Mechanics*, Vol. 29, to appear.

## Technical Presentations

"Transition Studies in Three-Dimensional Boundary Layers," by Th. Herbert, Invited Lecture, IUTAM Symposium on *Nonlinear Instability and Transition in Three-Dimensional Boundary Layers*, Manchester, UK, 17-20 July 1995.

"The Status of Applied Transition Analysis," by Th. Herbert, Invited Lecture, Royal Netherlands Academy of Arts and Sciences Colloquium on *Transitional Boundary Layers in Aeronautics; State of the Art and Future Directions of Research*, Amsterdam, Netherlands, December 6-8, 1995.

"Feedback Transition Control with On-the-fly Training of Neural Networks," by X. Fan, J. H. Haritonidis, and Th. Herbert, 48th Meeting of the APS-DFD, Irvine, CA, November 19 - 21, 1995.