Project #: C-36-X36
Center #: 10/24-6-R8169-0A0
Cost share #: 
Center shr #: 
Contract#: F49620-94-1-0362
Mod #: P00001
Prime #: 
Subprojects ? : N
Main project #: 
Rev #: 2
OCA file #: 
Work type : RES
Document : GRANT
Contract entity: GTRC

Project unit: COMPUTING
Unit code: 02.010.300
(404)894-3152

Sponsor/division names: AIR FORCE
Sponsor/division codes: 104

Award period: 940701 to 960930 (performance) 961130 (reports)

Sponsor amount
Contract value 0.00
Funded 0.00
Cost sharing amount 0.00

Total to date 161,742.00

Does subcontracting plan apply ?: N

Title: LEARNING MANEUVERS USING NEURAL NETWORK MODELS

PROJECT ADMINISTRATION DATA

OCA contact: Jacquelyn L. Bendall 894-4820
Sponsor technical contact

DR. MARC JACOBS
(202)767-5027

AFOSR/NM
110 DUNCAN AVENUE
ROOM B115
BOLLING AFB, DC 20332-8080

AFOSR/PKA
110 DUNCAN AVENUE
ROOM B115
BOLLING AFB, DC 20332-8080

Sponsor issuing office
JENNIFER BELL
(202)767-6836

Security class (U,C,S,TS) : U
ONR resident rep. is ACO (Y/N): N
Defense priority rating : X supplemental sheet
Equipment title vests with: Sponsor GIT X

Administrative comments -
MODIFICATION NO. P00001 EXTENDS POP TO 9/30/96. REPORTING REQUIREMENTS ARE REVISED. SCIENTIFIC OFC, PAYING OFC, AND ADM. OFC ADDRESSES ARE REVISED.
GEORGIA INSTITUTE OF TECHNOLOGY
OFFICE OF CONTRACT ADMINISTRATION

NOTICE OF PROJECT CLOSEOUT

Closeout Notice Date 01/24/97

Project No. C-36-X36__________

Center No. 10/24-6-R8169-0A0__

Project Director ATKESON C G__________

School/Lab COMPUTING____

Sponsor AIR FORCE/BOLLING AFB, DC______________________________

Contract/Grant No. F49620-94-1-0362__________

Contract Entity GTRC

Prime Contract No. ____________

Title LEARNING MANEUVERS USING NEURAL NETWORK MODELS______________________

Effective Completion Date 960930 (Performance) 961130 (Reports)

Closeout Actions Required: Y/N Submitted

Final Invoice or Copy of Final Invoice Y __________

Final Report of Inventions and/or Subcontracts Y __________

Government Property Inventory & Related Certificate Y __________

Classified Material Certificate N __________

Release and Assignment N __________

Other ________________________________ N __________

Date Submitted

Comments-------------------------------------------------------------------------

Subproject Under Main Project No. ____________

Continues Project No. ____________

Distribution Required:

Project Director Y

Administrative Network Representative Y

GTRI Accounting/Grants and Contracts Y

Procurement/Supply Services Y

Research Property Management Y

Research Security Services N

Reports Coordinator (OCA) Y

GTRC Y

Project File Y

Other ________________________________ N

NOTE: Final Patent Questionnaire sent to PDPI.

Christopher G. Atkeson
College of Computing, Georgia Institute of Technology
cga@cc.gatech.edu
Grant Number AFOSR F49-6209410362
1 Objectives

- To develop a practical nonparametric modeling approach, and to reduce the cost of nonlinear modeling and control system design.
- Real time nonparametric nonlinear system identification.
- Avoid negative interference.
- Develop nonlinear controller and estimator design algorithms based on nonparametric models.

2 Status of Effort

We have developed several important new nonparametric modeling techniques for high performance control of maneuvers. These techniques allow for real-time learning, and avoid negative interference when learning different maneuvers. The foundation of the new techniques is local modelling, where a locally weighted training criterion is used to train a local model for each query.

3 Accomplishments/New Findings

During the past year we have developed techniques to improve the performance of locally weighted modeling in the areas of:

- Modeling the bias and variance of locally weighted model predictions.
- Globally optimizing fit parameters such as distance metrics, ridge regression parameters, outlier rejection thresholds, and weighting function parameters.
- Identifying and eliminating locally irrelevant terms in the model.
- Locally optimizing fit parameters such as a smoothing parameter or bandwidth.
- Faster implementations that also use less memory.

3.1 State Of The Art

Research on nonlinear modeling techniques will advance the state of the art in nonlinear and learning control. A major challenge in the control of complex vehicles is dealing with the nonlinear dynamics of the vehicle. Learning algorithms are beginning to be applied for nonlinear control, with the most promising applications coming in situations classically handled with gain scheduling or with nonlinear inversion. These "classical" approaches exploit detailed mathematical models of the nonlinear dynamics; the promise of learning algorithms is that high fidelity nonlinear control might be implemented even when suitable first principle nonlinear models of the dynamics are lacking or expensive to obtain.
There is increasing interest in control system design based on nonlinear parametric models. Using such a model typically requires an assumption that the model structure is correct. This is rarely the case, and motivates the search for modeling techniques that can correct structural modeling errors. In cases where nonlinear models based on fixed structure neural networks have been shown to be able to approximate any function, large amounts of resources (exponential in the dimensionality of the state) have been required. Another approach is to add new resources as needed, by adding new parameters or terms to the model structure. Such techniques are being explored in the field of neural networks where new neurons are added to an existing net, and in statistics where approaches such as additive regression and projection pursuit add new terms to the model. These techniques, although promising, have not been adequately evaluated in adaptive control applications.

3.2 Approach

We have chosen to explore a different approach that avoids difficult issues such as choosing an appropriate model structure in advance of collecting the data. The locally weighted modeling approach simply stores data, which in a typical application would be the modeling errors of a parametric model based on knowledge of the plant. When a query is made to the parametric model, a new local correction model is formed using a locally weighted training criterion. This model is used to generate a correction to the output of the parametric model.

The locally weighted modeling approach has excellent asymptotic properties, but little is known about how well it will perform on finite data sets. We have applied it to the control of robots with excellent results.

3.3 Air Force Benefits

Success in this research will have several practical consequences. Learning systems may allow us to increase the performance range of a given vehicle. Learning systems can optimize performance, improving efficiency, range, and agility. Terrain may be followed more closely, and better pursuit and evasive maneuvers may be possible. Learning systems may also allow us to make use of less costly components in manned and unmanned vehicles, and allow the use of less expensive instrumentation and manufacturing processes to produce parts and vehicles with less exacting tolerances. Learning can correct for component inaccuracies as long as each component is individually repeatable. Learning systems may make complex manned and unmanned vehicles easier to fly, and easier to train pilots for. Specific pilot training modes can be developed. Learning systems may make unmanned vehicles usable for a wider range of missions and ground controller skills, and ground crew requirements for UAVs may be reduced. The research may also lead to a less expensive design process for control systems.

3.4 Future Work

We have shown that our nonparametric modelling techniques are successful in modeling nonlinear systems. However, an open question is how to use these nonparametric nonlinear
models to design robust control systems. The central thrust of this coming year’s research will be to explore how the nonparametric models can be used in the control of high performance maneuvers.

3.4.1 Nonlinear Controller Design Based On Dynamic Programming

Dynamic programming provides a methodology to design controllers and estimators for nonlinear systems. However, general dynamic programming is intractable. We propose using dynamic programming in tubes around the trajectory of a maneuver, and in bubbles around a goal state. We will use sophisticated representations of high dimensional sub-manifolds to enable dynamic programming in higher dimensional spaces than are currently possible.

3.4.2 Robust Controller Design And Exploration

We have derived the bias and variance for our local modeling approaches, and expressions for the uncertainty of local model parameters. These techniques can be used directly in robust controller design approaches, and in dynamic programming to choose how to explore optimally, in addition to controlling optimally.

4 Personnel Supported

Salary support was provided to the PI: Prof. Christopher G. Atkeson.

5 Publications


• Christopher G. Atkeson, Andrew W. Moore, Stefan Schaal, *Locally Weighted Learning*, submitted to Artificial Intelligence Review.


6 Interactions/Transitions

6.1 Presentations not covered in *Publications*


6.2 Consultative and Advisory Functions

Member, review panel, National Science Foundation program on Robotics and Machine Intelligence. Reviewed approximately 40 proposals. Met in Washington DC April 5. Program manager is Howard Moraff.

6.3 Transitions: Technology Transfer And Dual Use

Colleagues have applied the techniques we have developed in several industrial process control applications, with excellent results. We have been developing a demonstration of these techniques on a state of the art 7 degree of freedom robot arm. We will make the control code we develop for this arm available to other implementors who would like to know the details of our implementation techniques.

7 Inventions and Patents

None.

8 Honors/Awards

None.
Principal Investigator Annual Data Collection (PIADC) Survey Form

Please submit the requested data for the period 1 October 1994 through 30 September 1995. Request you follow the data requirements and format instructions below. This data is due to your AFOSR program manager NLT 30 September 1995.

NOTE: If there is insufficient space on this survey to meet your data submissions, please submit additional data in the same format as identified below.

PI DATA

Name (Last, First, MI): Atkeson, Christopher G.
Institution Georgia Institute of Technology
Contract/Grant No. F49-6209410362

NUMBER OF CONTRACT/GRANT CO-INVESTIGATORS

Faculty 1, Post Doctorates 0, Graduate Students 0, Other 0.

PUBLICATIONS RELATED TO AFOREMENTIONED CONTRACT/GRANT

NOTE: List names in the following format: Last Name, First Name, MI
Include: Articles in peer reviewed publications, journals, book chapters, and editorships of books.
Do Not Include: Unreviewed proceedings and reports, abstracts, "Scientific American" type articles, or articles that are not primary reports of new data, and articles submitted or accepted for publication, but with a publication date outside the stated time frame.

Name of Journal, Book, etc.: Neurocomputing
Title of Article: Memory-Based Neural Networks For Robot Learning
Author(s): Atkeson, Christopher, G.; Schaal, Stefan
in press.

Name of Journal, Book, etc.: Transactions on Neural Networks
Title of Article: Implementing Projection Pursuit Learning
Author(s): Zhao, Ying; Atkeson, Christopher, G.
in press.

Name of Journal, Book, etc.: Journal of Motor Behavior
Title of Article: One-handed Juggling: Dynamical Approaches to a Rhythmic Movement Task
Author(s): Schaal, Stefan, Sternad, Dagmar; Atkeson, Christopher, G
in press.
HONORS/AWARDS RECEIVED DURING CONTRACT/GRANT LIFETIME

Include: All honors and awards received during the lifetime of the contract or grant, and any life achievement honors such as (Nobel prize, honorary doctorates, and society fellowships) prior to this contract or grant.

Do Not Include: Honors and awards unrelated to the scientific field covered by the contract/grant.

None.

Christopher G. Atkeson
College of Computing, Georgia Institute of Technology
cga@cc.gatech.edu
Grant Number AFOSR F49-6209410362
1 Abstract

During the final year 1995-1996 of the grant *Nonparametric Modeling and Control of High Performance Maneuvers* the techniques developed in previous years were implemented on a nonlinear testbed, and worked well. The nonlinear testbed was a complex seven degree of freedom robot arm. The techniques were capable of learning maneuvers both autonomously and from demonstrations by experts. This implementation demonstrates the potential of control design techniques based on learned local nonparametric models.

2 Objectives

- Develop a practical nonparametric modeling approach, and reduce the cost of nonlinear modeling and control system design.
- Real time nonparametric nonlinear system identification.
- Avoid negative interference.
- Develop nonlinear controller and estimator design algorithms based on nonparametric models.

3 Status of Effort

We have implemented several nonparametric modeling techniques for high performance control of maneuvers on a robot arm, which serves as a nonlinear testbed. These implementations demonstrate real-time learning, and avoid negative interference when learning different maneuvers. The foundation of the new techniques is local modeling, where a locally weighted training criterion is used to train a local model for each query.

4 Accomplishments/New Findings

During the past year we have implemented our techniques on a nonlinear testbed, a robot arm. This implementation helps evaluate and validate our approaches to:

- modeling the bias and variance of locally weighted model predictions.
- globally optimizing fit parameters such as distance metrics, ridge regression parameters, outlier rejection thresholds, and weighting function parameters.
- identifying and eliminating locally irrelevant terms in the model.
- locally optimizing fit parameters such as a smoothing parameter or bandwidth.
4.1 State Of The Art

Research on nonlinear modeling techniques will advance the state of the art in nonlinear and learning control. A major challenge in the control of complex vehicles is dealing with the nonlinear dynamics of the vehicle. Learning algorithms are beginning to be applied for nonlinear control, with the most promising applications coming in situations classically handled with gain scheduling or with nonlinear inversion. These "classical" approaches exploit detailed mathematical models of the nonlinear dynamics; the promise of learning algorithms is that high fidelity nonlinear control might be implemented even when suitable first principle nonlinear models of the dynamics are lacking or expensive to obtain.

There is increasing interest in control system design based on nonlinear parametric models. Using such a model typically requires an assumption that the model structure is correct. This is rarely the case, and motivates the search for modeling techniques that can correct structural modeling errors. In cases where nonlinear models based on fixed structure neural networks have been shown to be able to approximate any function, large amounts of resources (exponential in the dimensionality of the state) have been required. Another approach is to add new resources as needed, by adding new parameters or terms to the model structure. Such techniques are being explored in the field of neural networks where new neurons are added to an existing net, and in statistics where approaches such as additive regression and projection pursuit add new terms to the model. These techniques, although promising, have not been adequately evaluated in adaptive control applications.

4.2 Approach

We have chosen to explore a different approach that avoids difficult issues such as choosing an appropriate model structure in advance of collecting the data. The locally weighted modeling approach simply stores data, which in a typical application would be the modeling errors of a parametric model based on knowledge of the plant. When a query is made to the parametric model, a new local correction model is formed using a locally weighted training criterion. This model is used to generate a correction to the output of the parametric model.

The locally weighted modeling approach has excellent asymptotic properties, but little is known about how well it will perform on finite data sets. We have applied it to the control of robots with excellent results.

4.3 Air Force Benefits

Success in this research will have several practical consequences. Learning systems may allow us to increase the performance range of a given vehicle. Learning systems can optimize performance, improving efficiency, range, and agility. Terrain may be followed more closely, and better pursuit and evasive maneuvers may be possible. Learning systems may also allow us to make use of less costly components in manned and unmanned vehicles, and allow the use of less expensive instrumentation and manufacturing processes to produce parts and vehicles with less exacting tolerances. Learning can correct for component inaccuracies as long as each component is individually repeatable. Learning systems may make complex manned and unmanned vehicles easier to fly, and easier to train pilots for. Specific pilot
training modes can be developed. Learning systems may make unmanned vehicles usable for a wider range of missions and ground controller skills, and ground crew requirements for UAVs may be reduced. The research may also lead to a less expensive design process for control systems.

4.4 Future Work
We are in the process of writing up this work as papers and as a final report for this grant.

5 Personnel Supported
Salary support was provided to the PI: Prof. Christopher G. Atkeson and to a graduate student, Gary Boone.

6 Publications


• Atkeson, C. G., and S. Schaal, "Memory-Based Neural Networks For Robot Learning", Neurocomputing, in press.

• Zhao, Y., and C. G. Atkeson, "Implementing Projection Pursuit Learning", Transactions on Neural Networks, in press.


• Atkeson, C. G., A. W. Moore, and S. Schaal, "Locally Weighted Learning," Artificial Intelligence Review, in press

• Atkeson, C. G., A. W. Moore, and S. Schaal, "Locally Weighted Learning for Control", Artificial Intelligence Review, in press.


7 Interactions/Transitions

7.1 Presentations not covered in Publications
None.

7.2 Consultative and Advisory Functions
None.

7.3 Transitions: Technology Transfer And Dual Use
None.

8 Inventions and Patents
None.

9 Honors/Awards
None.
August 5, 1996

Air Force Office of Scientific Research
Ms. Jennifer Bell
AFOSR / PKA
110 Duncan Avenue, Suite B115
Bolling AFB, DC 20332-0001

Subject: Grant No. F49620-94-1-0362

Dear Ms. Bell:

Enclosed is the interim Financial Status Report (SF-269A) for the above noted grant for the period July 1, 1994 through June 30, 1995.

If you have any questions or require additional information, please contact Kate Edwards at (404) 894-5522.

Sincerely,

David V. Welch, Director
Grants and Contracts Accounting
DVW/ke

Enclosures

File: C-36-X36/246R81690A0
Wanda Simon, OCA, Mailcode 0420

Office of Grants and Contracts Accounting
190 Bobby Dodd Way
Atlanta, Georgia 30332-0259 U.S.A.
PHONE 404-894-4624 FAX 404-894-5519
RISK MANAGEMENT 404-894-4626

A Unit of the University System of Georgia An Equal Education and Employment Opportunity Institution
**FINANCIAL STATUS REPORT**  
**SHORT FORM**  

1. **FEDERAL AGENCY AND ORGANIZATIONAL ELEMENT TO WHICH REPORT IS SUBMITTED**  
AFOSR  

2. **FEDERAL GRANT OR OTHER IDENTIFYING NUMBER ASSIGNED BY FEDERAL AGENCY**  
F49620-94-1-0362  

3. **RECIPIENT ORGANIZATION (Name and complete address, including ZIP code)**  
GEORGIA TECH RESEARCH CORPORATION, P.O. BOX 100117, ATLANTA, GA 30384  

4. **EMPLOYER IDENTIFICATION NUMBER**  
58-0603146  

5. **RECIPIENT ACCOUNT NUMBER OR IDENTIFYING NUMBER**  
C-36-X36/246R8169GA0  

6. **PROJECT/GRANT PERIOD**  
FROM: (Month, Day, Year)  
7/1/94  
TO: (Month, Day, Year)  
6/30/96  

7. **BASIS**  
X CASH  

8. **RECIPIENT ACCOUNT NUMBER OR IDENTIFYING NUMBER**  
C-36-X36/246R8169GA0  

9. **PERIOD COVERED BY THIS REPORT**  
FROM: (Month, Day, Year)  
7/1/94  
TO: (Month, Day, Year)  
6/30/95  

10. **TRANSACTIONS:**  

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<td>f. Federal share of unliquidated obligations</td>
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<td>e. Federal Share</td>
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12. **Remarks:** Attach any explanations deemed necessary or information required by Federal sponsoring agency in compliance with governing legislation.  

3. **Certification:** I certify to the best of my knowledge and belief that this report is correct and complete and that all outlays and unliquidated obligations are for the purposes set forth in the award documents.  

4. **Typed or Printed Name and Title**  
David V. Welch, Director  
Grants and Contracts Accounting  

5. **Telephone (Area code, number and extension)**  
(404) 894-2629  

6. **Signature of Authorized Certifying Official**  

7. **Date Report Submitted**  
8/5/96  

8. **Questions concerning this report should be directed to Kate Edwards (404) 894-5522.**


**Abstract:**

We developed several nonparametric modeling techniques as well as nonlinear controller design techniques. We successfully implementing these techniques on a robot arm. We used a locally weighted modeling approach as the basis of our nonparametric modeling technique. Locally weighted modeling avoids negative interference by retaining the original training data, so the approach is adaptive to changing data distributions. We used sophisticated representations of high dimensional sub-manifolds to enable dynamic programming in higher dimensional spaces than are currently possible.
1 Objectives

There were two major objectives in this project: to develop a practical nonparametric modeling approach and a complementary nonlinear control design approach for high performance maneuvers. The desired characteristics of the nonparametric modeling approach were:

- The approach can be applied automatically or with minimal human supervision.
- The approach can be applied for online system identification.
- The approach does not suffer from interference.
- The approach reduces the cost of nonlinear modeling.

The desired characteristics of the nonlinear control design approach were:

- The approach can be applied automatically or with minimal human supervision.
- The controller designs can be based on the identified nonparametric models.
- The approach reduces the cost of nonlinear controller design.

The approaches developed were to be explored theoretically, in simulation, and in an actual implementation.

2 State Of The Art

Research on nonlinear modeling techniques advances the state of the art in nonlinear and learning control. A major challenge in the control of complex vehicles is dealing with the nonlinear dynamics of the vehicle. Learning algorithms are beginning to be applied for nonlinear control, with the most promising applications coming in situations classically handled with gain scheduling or with nonlinear inversion. These “classical” approaches exploit detailed mathematical models of the nonlinear dynamics; the promise of learning algorithms is that high fidelity nonlinear control might be implemented even when suitable first principle nonlinear models of the dynamics are lacking or expensive to obtain.

Using a nonlinear parametric model typically requires an assumption that the model structure is correct. This is rarely the case, and motivates the search for modeling techniques
that can correct structural modeling errors. In cases where nonlinear models based on fixed structure neural networks have been shown to be able to approximate any function, large amounts of resources (exponential in the dimensionality of the state) have been required. Another approach is to add new resources as needed, by adding new parameters or terms to the model structure. Such techniques are being explored in the field of neural networks where new neurons are added to an existing net, and in statistics where approaches such as additive regression and projection pursuit add new terms to the model. These techniques, although promising, have not been adequately evaluated in adaptive control applications.

3 Approach

3.1 Nonparametric Modeling Based On A Locally Weighted Criterion

We have chosen to explore a different approach that avoids difficult issues such as choosing an appropriate model structure in advance of collecting the data [4,7]. The locally weighted modeling approach simply stores data, which in a typical application would be the modeling errors of a parametric model based on knowledge of the plant. When a query is made to the parametric model, a new local correction model is formed using a locally weighted training criterion:

\[ C_q(\beta) = \sum_i [(f(x_i, \beta) - y_i)^2 K(d(x_i, q))] \]  

(1)

the ith training data point has an input vector \( x_i \) and an output \( y_i \); \( f() \) is a model structure with a parameter vector \( \beta \), \( K() \) is the weighting or kernel function such as a one dimensional Gaussian, and \( d(x_i, q) \) is the distance between the data point \( x_i \) and the query \( q \). Using this training criterion, \( f(x, \beta) \) becomes a local model, and can have a different set of parameters \( \beta \) for each query point \( q \) [7].

The locally weighted modeling approach has excellent asymptotic properties, but little is known about how well it will perform on finite data sets. We have applied it to the control of robots with excellent results [1,2,8].

Linear systems require persistent excitation for accurate system identification. With nonlinear systems and an approximately correct model structure, the parameters identified depend on the data distribution. Negative interference is the loss of the ability to fit a previous data distribution because of training on a new data distribution. Locally weighted modeling avoids negative interference by retaining the original training data, so the approach is adaptive to changing data distributions [7].

3.2 Nonlinear Controller Design Based On Dynamic Programming

Dynamic programming provides a methodology to design controllers and estimators for nonlinear systems. However, general dynamic programming is intractable. We explored using dynamic programming in tubes around the trajectory of a maneuver, and in bubbles around
a goal state. We used sophisticated representations of high dimensional sub-manifolds to enable dynamic programming in higher dimensional spaces than are currently possible [3,9,10].

4 Results

We developed several nonparametric modeling techniques [1,4,6,7] as well as controller design techniques [2,3,8,9,10] for high performance control of maneuvers. We explored these schemes in simulation as well as implementing them on a nonlinear testbed. The nonlinear testbed was a complex seven degree of freedom robot arm. These implementations worked well, demonstrated real-time learning, and avoided negative interference when learning different maneuvers. The techniques were capable of learning maneuvers both autonomously and from demonstrations by experts. These implementations demonstrated the potential of control design techniques based on learned local nonparametric models.

We developed and implemented techniques to improve the performance of locally weighted modeling in the areas of:

- Modeling the bias and variance of locally weighted model predictions. Our predictions are linear in the data, leading to straightforward estimates of prediction bias, variance, and confidence intervals.
- Globally optimizing fit parameters such as distance metrics, ridge regression parameters, outlier rejection thresholds, and weighting function parameters.
- Identifying and eliminating locally irrelevant terms in the model.
- Locally optimizing fit parameters such as a smoothing parameter or bandwidth.
- Faster implementations that also use less memory based on using “receptive fields”, each of which maintains a local model.

4.1 Air Force Benefits

Success in this research can have several practical consequences. Learning systems can allow us to increase the performance range of a given vehicle. Learning systems can optimize performance, improving efficiency, range, and agility. Terrain may be followed more closely, and better pursuit and evasive maneuvers may be possible. Learning systems may also allow us to make use of less costly components in manned and unmanned vehicles, and allow the use of less expensive instrumentation and manufacturing processes to produce parts and vehicles with less exacting tolerances. Learning can correct for component inaccuracies as long as each component is individually repeatable. Learning systems may make complex manned and unmanned vehicles easier to fly, and easier to train pilots for. Specific pilot training modes can be developed. Learning systems may make unmanned vehicles usable for a wider range of missions and ground controller skills, and ground crew requirements for UAVs may be reduced. The research can lead to less expensive design processes for control systems.
5  Future Work

We have shown that our nonparametric modelling techniques are successful in modeling nonlinear systems. However, an open question is how to use these nonparametric nonlinear models to design robust control systems. We have derived the bias and variance for our local modeling approaches, and expressions for the uncertainty of local model parameters. These techniques can be used directly in robust controller design approaches, and in dynamic programming to choose how to explore optimally, in addition to controlling optimally.

6  Personnel Supported

Salary support was provided to the PI: Prof. Christopher G. Atkeson and to a graduate student, Gary Boone.

7  Publications


8 Interactions/Transitions

8.1 Presentations not covered in Publications


8.2 Consultative and Advisory Functions

Member, review panel, National Science Foundation program on Robotics and Machine Intelligence. Reviewed approximately 40 proposals. Met in Washington DC April 5, 1995. Program manager is Howard Moraff.

8.3 Transitions: Technology Transfer And Dual Use
None.

9 Inventions and Patents
None.

10 Honors/Awards
None.