Investigation of Multi-Dimensional Interpolation Methodologies for Vehicle Maneuvering and Design

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Simulations of two depth-changing maneuvers were conducted to provide data for neural network training. Details of this effort are provied in Ref. 1.

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Abstract

Recurrent and feedforward neural networks were studied and compared for their ability to adequately capture dynamics from a physics-based computational model of submarine maneuvering dynamics. The comparison was done using *one* trajectory of a rise maneuver. Very good approximation was achieved with recurrent neural networks. The results with modular feedforward networks were not as good, but were reasonable. When the networks were tested for an unseen dive maneuver, the response followed the shape of the desired response but there were large overshoots. This preliminary study demonstrated that it is possible to learn dynamics from computational models, that recurrent neural networks are much better suited for this task, and that additional data are required for good generalization. However, an approach for very limited training data set design was developed for further investigation. The applications of this approach are numerous, including online use of detailed models, rapid iterative design update, improved control of a submarine and eventually its noise characteristics, condition-based maintenance in the presence of aging and degrading parts, and potentially, damage assessment and mitigation in hostile situations.

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Background

Application of artificial neural networks has proved to be very useful in the solution of several difficult non-linear system modeling, nonlinear control and optimization problems. In such cases, they typically achieve much better solutions than conventional methods, usually exhibiting greater accuracy, improved performance and reduced need for training data. Many types of neural networks have been developed to satisfy demands from a large variety of applications. They can be classified in various ways, e.g., according to flow of information in the networks, feedforward or feedback, or based on method of determining the structure or connections in the network, supervised or unsupervised training. Feedforward networks and supervised training are very useful for classification. Unsupervised learning is usually used for feature extraction. Feedback networks are most often employed for modeling dynamical systems or in non-stationary signal processing. However, the context of time variation of the dynamics can also be learned to a limited extent using time-delay feedforward neural networks. Much research is still on-going to address the issues of the choice of time delays, the size and topology of the network, the neuron activation functions and the training methods. Furthermore, judicious choice of permissible training error leads to good performance of the network with new data (generalization). One type of feedback neural network is called the recurrent neural network, in which only the outputs of the network are fed back to the input of the network. While the training of such a neural network is often easier than a network with internal feedback, it offers many advantages over feedforward networks. However, the issues of network size, topology, activation functions, and training method still require careful attention and familiarity with the problem domain as well as the characteristics of recurrent neural networks.

Neural Networks for Trajectory Prediction

It is not possible to calculate exactly the motion of a submarine based solely on measurements and their substitution into formulas. The number of variables necessary to be considered is too large (e.g. the variables that describe the environment), and it is not possible to describe the intricate details of the submarine motion with an explicit equation. Very large numerical models must be developed to capture the fine details of submarine dynamics. Such models are not used regularly at this time due to their complexity. Often, experimental model-scale results are used to characterize the vehicle motion and determine the submerged operating envelope (SOE). While the details of the submarine dynamics are an integral part of the numerical models, they may not be necessary for prediction of each unique trajectory. Rather, neural networks may avoid the time consuming computations through far simpler nonlinear mappings that can adequately approximate the model and predict the motion of the submarine. The neural networks can be trained with either data from computations or experiments. See Ref. 2 for an example of the latter application. However, the number of training data sets depends on the form the neural net employed. A possible training strategy is shown in Figure 1, where it is hypothesized that training with sufficiently varied training sets will provide an adequate mapping of the desired maneuvering space.

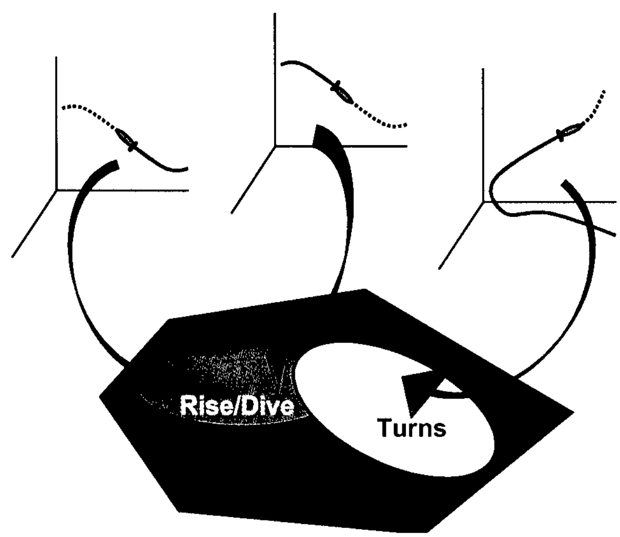

Figure 1. Maneuvering Space

Neural networks have been shown to be universal approximators. In addition, neural networks are fast, which is important in an operational situation where prediction is needed immediately. We have shown earlier that recurrent neural networks were useful in interpolating trajectories of a submarine undergoing various maneuvers, including crashback (Appendix A). The specific type of network employed was the polynomial recurrent neural network of Barron Associates, Inc. (BAI) accessible with their package GNOSIS. Some of the challenges for neural networks are:

- Determine neural network type: feedforward or recurrent, etc
- Single network or Modular networks
- Local vs. Global influences: input selection
- Prevention of overtraining
- Training with small training data sets

A significant part of project efforts were focused on the task of developing neural networks for trajectory prediction. In addition, we found that the alternative approach of trajectory prediction via the prediction of forces and moments as well as angular rates offers much more detailed information about the submarine dynamics and greater confidence in the prediction estimates. A novel approach to address this problem is described below along with the results of the study thus far. This work was performed at the ARL Penn State University. The efforts performed by Barron Associates are reported in Appendix A.

In addition to the polynomial recurrent neural networks several feedforward neural networks were studied to assess their ability to capture the computational model dynamics. Comparisons primarily focused on radial basis function (RBF) networks and time-delay neural networks (TDNN). Moreover, several modules of feedforward neural networks were trained on various sections of the submarine and on various parts of the maneuver. Then the outputs of the modules were combined to get a composite output, which provided reasonable results.

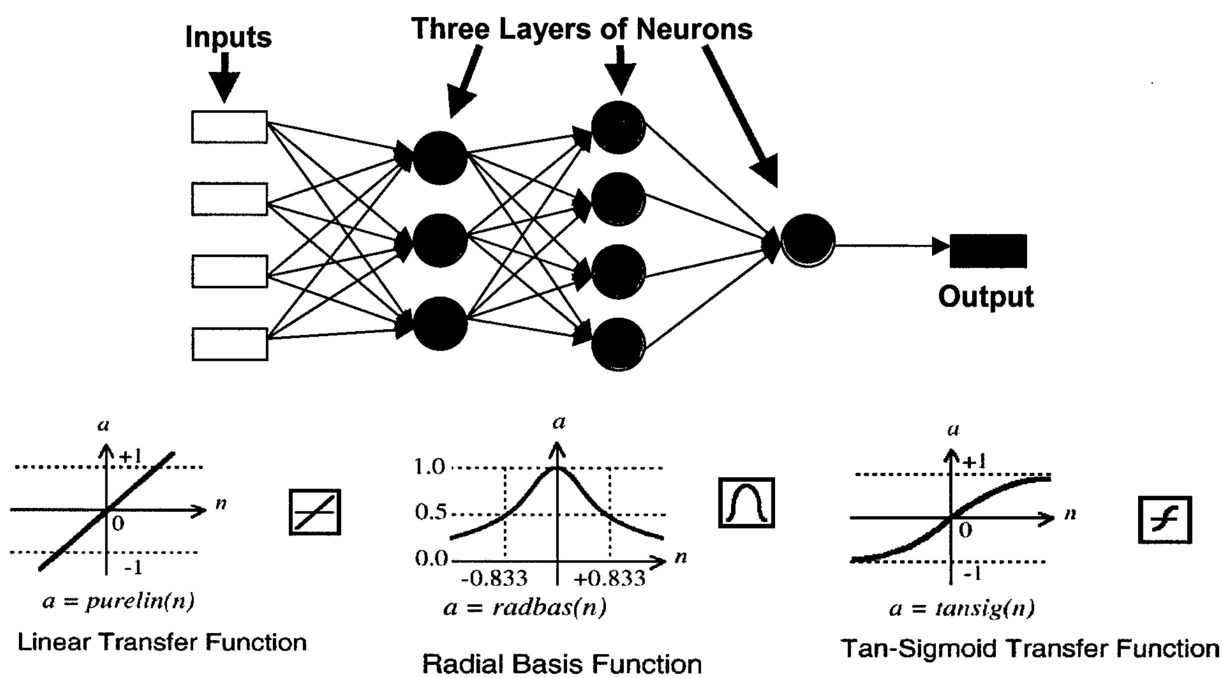

Figure 2. Three-layer neural network and standard activation functions

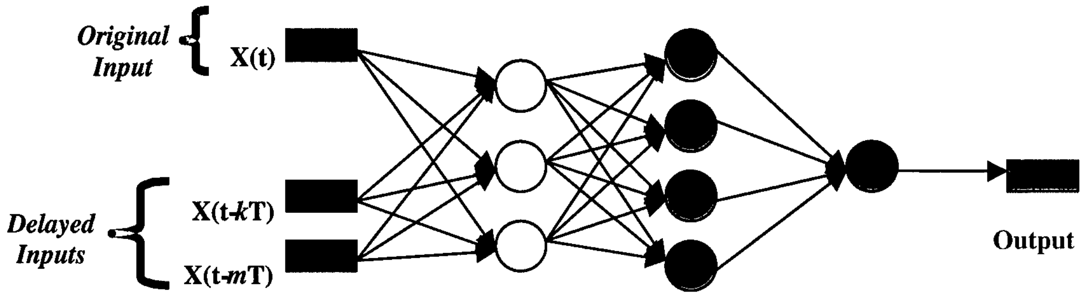

Figure 3. Time-delay neural network (TDNN).

Modular Network Architecture

The dynamics of the submarine are very complex and it is unreasonable to expect a single network to learn them sufficiently to offer adequately accurate prediction. Furthermore, it is important to design the networks to allow them to exploit the variety of interactions that lead to specific trajectories resulting from different types of maneuvers. We decided to save the data during a computational run dividing the submarine into various appendage and hull sections. These data are used to train neural modules dedicated to learning the dynamics of the individual sections. However, it is also possible to train the networks with data from sections that have the greatest impact during specific maneuvers. This approach allows us to manage the need for enormous training data sets required for accurate predictions. Additionally, it can potentially provide the basis for future speedups in simulation time. Finally, it offers an attractive possibility of on-line implementation of the model in the analysis and control systems of a submarine.

Prediction Results

To systematically address the problem of trajectory prediction, we chose a fixed prediction time window of 0.3 units of non-dimensional time. The prediction window was chosen to provide a reasonable trade-off between prediction time and prediction performance. Data for a rise maneuver were utilized for comparing the performance of recurrent and feedforward neural networks as well as some statistical methods. Training was done on the first 80% of the data with sampling rate of about 150 Hz, which is reduced by a factor of 10 as compared to the sampling rate required for the data generation. The remaining data were saved for testing prediction performance. We trained recurrent networks, with GNOSIS, to predict depth (z) using the forces on the stern planes as inputs and adding other inputs (e.g., pitch rate, roll rate, etc.) to study their effect on prediction performance. GNOSIS offers many options to allow the designer to customize the network to the task at hand. We varied the node degree, node type (polynomial type), and input and output time delays to study their effects on prediction. We observed better performance with lower node degree but multi-linear

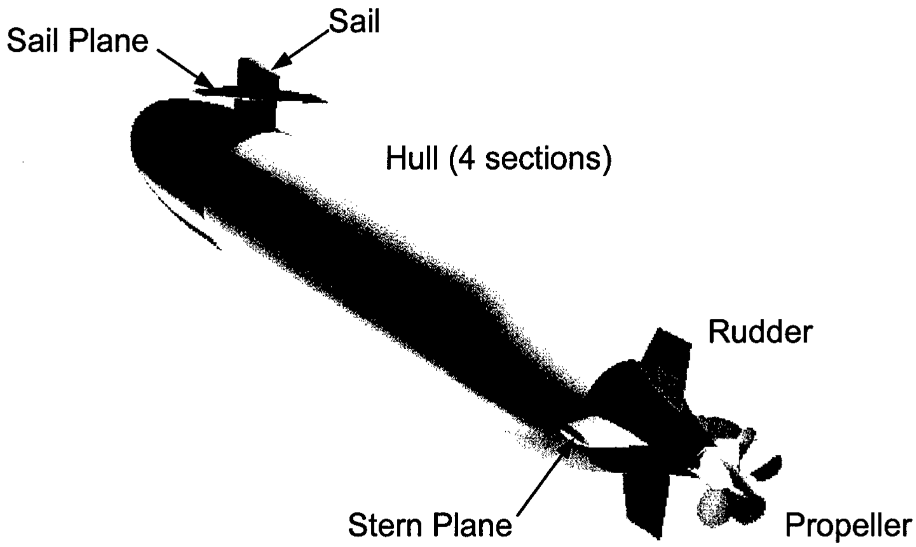

Figure 4. Submarine sections.

node type (allows cross-terms). This was also the case with prediction of the pitch and roll rates. Additional inputs also helped but the improvement was not very pronounced since the prediction error was very low: the training error was less than 0.01 % and prediction error was less than 1%. Indeed, improper selection of parameters and inputs would lead to much greater error. For example, for predicting depth the best performance was obtained with the following inputs: time, propeller force, stern plane force and yaw angle. Adding other angles as inputs degrades the prediction.

The study of feedforward networks for prediction was done using MATLAB and the Neural Networks Toolbox. The results of predicting depth using six-DOF data were very good. Best performance was obtained when time-delay neural networks were employed. Training was performed using adaptive gradient descent with momentum and also using the Levenburg-Marquadt method. In each case, error backpropagation training was performed. Similar prediction results were obtained for depth prediction. It was also observed that prediction performance worsens as the network complexity increases beyond a certain point. Similarly, forcing extremely low (much less than 0.01 %) training error actually results in very poor prediction performance. Best performance was obtained with two hidden layers and radial basis activation functions. In most cases, 3% noise was added to the training data to prevent overtraining, and improve generalization.

Numerous cases were studied and compared. Representative results are shown below for recurrent neural networks and time-delay feedforward neural networks. Radial basis function networks did not perform as well as a TDNN. If training error target was set very low, the approximation was improved but prediction (generalization within trajectory) was poorer. As the size of the network was increased performance improved but if the size of the network was too large the performance actually worsened due to overtraining. These observations apply to both feedforward and recurrent neural networks.

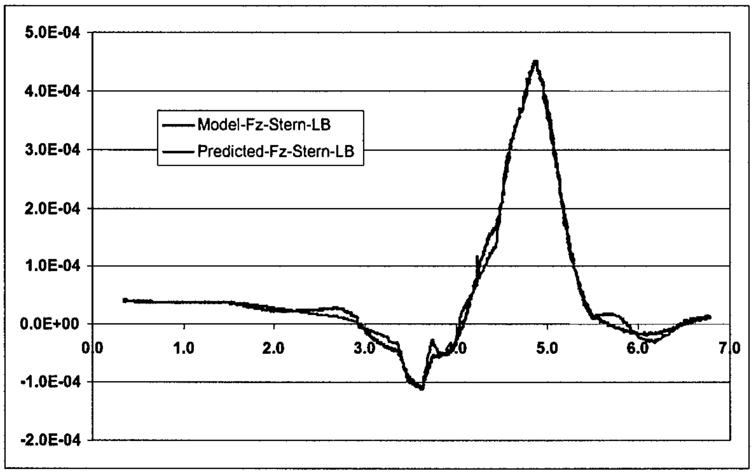

Figure 5. Recurrent neural networks provided excellent approximation to the computational model. Force (Fz) on stern plane vs. time.

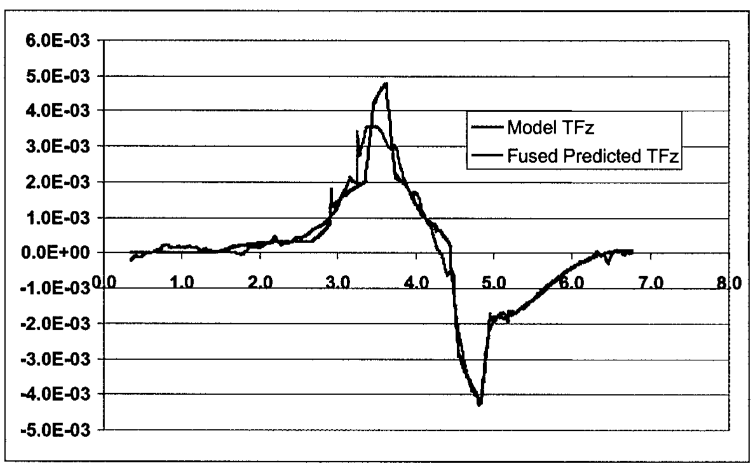

Figure 6. Modular feedforward neural networks provided reasonable approximation to the computational model. Total force (TFz) vs. time.

Once the networks were trained they were also tested with a dive maneuver to check generalization to unseen maneuvers. The results were not good as was expected. However, it was encouraging to see that the recurrent network followed the shape of the response, though there were significant overshoots.

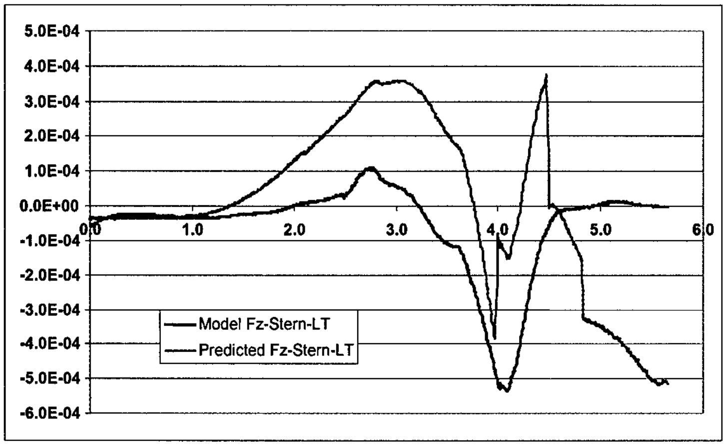

Figure 7. Recurrent neural networks response for (unseen) DIVE maneuver. Force (Fz) on stern plane vs. time.

Conclusions and Future work

We have formulated an approach to the design of training data to learn the operating envelope of the submarine adequately to provide accurate predictions for a variety of maneuvers. The approach employs concepts from the theory of system identification and control of nonlinear dynamical systems. Furthermore, hybrid neural methods employing neural and rule-based systems will be employed to further mitigate the explosion of data requirements as we incorporate more maneuvers and try to exploit additional high-fidelity information provided by the computational model.

Prediction of dynamics was found to be much more complex and difficult than interpolation. A comprehensive approach, which is hierarchical and modular, was developed and studied with extremely limited data. Multiple methods were studied and compared. Recurrent networks were found to be more suitable than feedforward networks for capturing the dynamics of submarines from a computational model. The need for more data for prediction under maneuvers has been established. However, using techniques from control systems and system identification for nonlinear systems parsimonious data set design can be achieved for maximum training and generalization performance. Limited incorporation of interaction among forces from various sections was explored and was found to be very promising. Finally, the systematic use domain knowledge would require use of fuzzy logic methods in conjunction with neural networks.

Acknowledgements

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were also displayed at Penn State's Eighth Annual Undergraduate Research Fair on March 29 and 30, 1999.

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