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MODELLING AND CONTROL OF SHIPS USING NEURAL NETWORKS

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ABSTRACT.

Artificial Neural Networks are applied to the design of a ship steering control system. A local model network is used to represent the plant. A radial basis function network is trained as a controller. Performance is demonstrated by a series of simulation studies.

Key words: **Ship control modeling, Neural Networks.**

Introduction:

During the past few year some very useful papers have appeared in the literature on the applicability of artificial neural networks (ANNs) for ship steering control (1,2). Almost all of these papers have made used of a multi-layer perceptron (MLP) architecture and have trained neural networks by using the superviseed learning of ANNs. This paper is based on the same approach but it is different in two respects: (a) we investigatie the applicability of radial basis function networks (RBFNs) instead of MLPs for developing ANN controllers at different speeds (b) we also investigvate the potential of local model networks (LMNs) for modelling the ship dynamics. Local modol networks or operating regime based models, have an architectue which relates closely to ANNs. Such networks have already proved valueable in other applications involving the modelling of systems in which the dynamic characteritics can vary Psignificantly with the system operating conditions (3,4).,

1. Ship Steering Control

The main purpose of a ship steering control system is to generate an appropriate rudder signal for controlling the heading angle of a ship. The controllers can be designed to perform two entirely different functions: course keeping and course changing. In course changing, the control system should provide good maneuverability, whereas in course keeping the ship should stay on a set course. Particular consideration has been given to the course changing problem in this paper. A model reference approach has been used as shown in Figure 1, where Ψ_r is the reference heading, Ψ_d is the desired heading, Ψ is the actual heading and δ is the rudder angle (all in degrees).

A second order or third order reference model is used to generate the desired heading. The steering machine includes rudder deflection angle limiting and rudder rate limiting.

Many ship models have been proposed in the literature and the most popular among these is the Nomoto's model given by (5).

$$T\Psi+\Psi=K\delta$$

Where K is a gain constant and T is the time constant of the ship

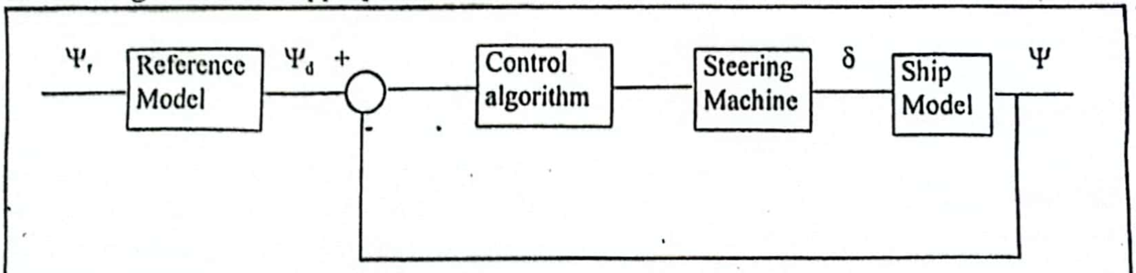

Figure 1: Ship steering control system

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It should be noted that the parameters K an T depend upon the forward speed of the ship and can be made dimensionless with respect to speed variations by applying the transformations $K=K_0 (U/L)$, $T=T_0 (L/U)$.

Where K_0 and To are the gain and time constant respectively at a speed U m/sec., L is the length of the ship.

3. Radial Basis Function Networks:

RBF networks have seen a number of successful applications during recent years. The popularity of these networks is because of their distinctive properties of best approximation, simple network structure and efficient learning procedure [6,7,8,]

An RBFN is multilayer feedforward network with a single hidden layer. Radial basis functions are used as the activation functions and these are commonly of Gaussian exponential form. A number of algorithms have been developed for the training of these networks. In this paper, we use the orthogonal least square (OLS) algorithm (9). This algorithm selects a set of RBF centres as a subset of the training data vectors and computes the optimal set of weights and biases of the network.

4. Local Model Networks:

Local model networks were developed by Johansen and Foss (10) and may be regarded as special form of RBFN. An LMN is a set of models weighted by some activation function (see Figure 2). The same input signal is fed to each model and outputs are weighted according to some scheduling variable or variables, ϕ,

$$y(t)=\sum_{i=1}^{n} y_i(t)\rho i(\phi)$$

Where y(t) is the model network output, $Pi(\phi)$ is the basis function of the ith model, n is the number of models, and yi(t) is the lcoal model output and a function of time. The weighting or activation of each local model is calculated using the activation function which is a function of the scheduling variable and could be a system state variable, an input variable or some other system parameter. The basis functions are normalised so that their sum is equal to unity at every point. The individual component models of a local model network can be linear or no linear dynamic models of varying structure and can be continuous or discrete.

There are two components for identifying an LMN – its structure and its parameters. The network structure is the numbner of localmodels, their respective centres and widths, and the activation function. The local model parameters describe the local models themselves. These parameters could be the complete set of coefficients of a linear model, numerical parameters of a nonlinear model, or even switches which altered the local model structures. Further details can be found in (10,11).

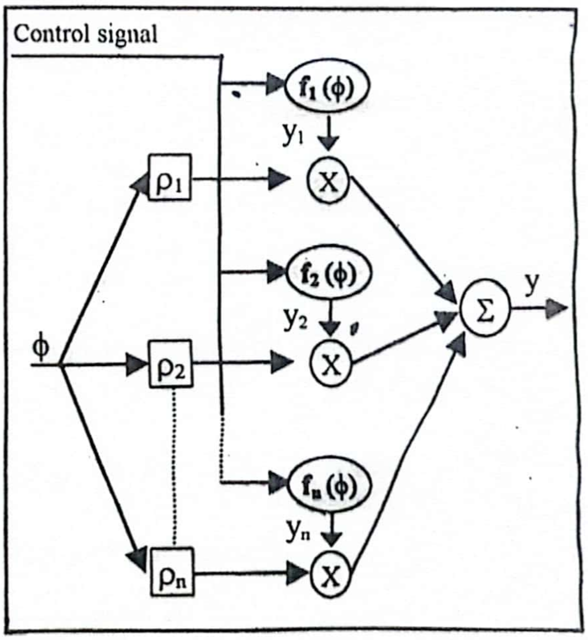

Figure 2: General architecture of LMN

5. Simulation studies:

This section describes the details of developing RBF controller to control the heading of a tanker of length 310m, and demonstrates the use of the LMNs for modelling the dynamics of the ship. The parameters of the tanker at a speed of 4.2m/sec are T=13.37, and K=-7.93(12).

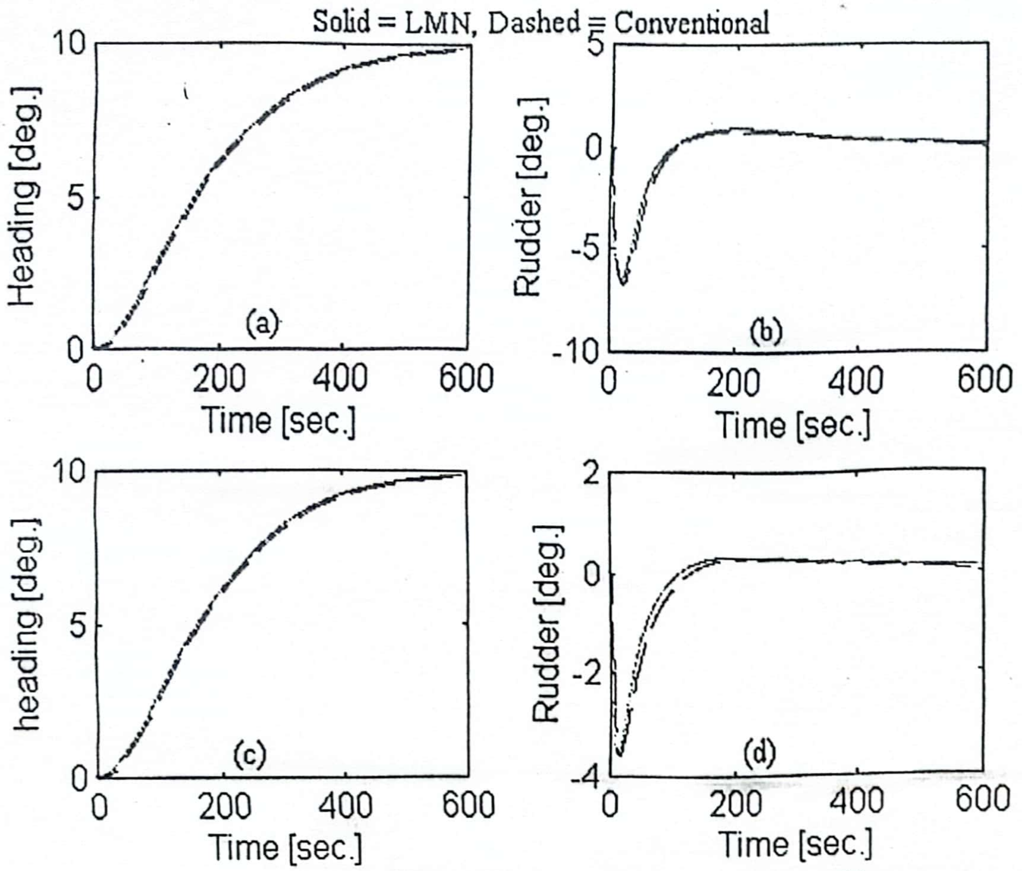

Figure 3: (a) Heading response at 5m/sec (b) the corresponding rudder response. (c) Heading response at 10m/sec (d) the corresponding rudder response.

We used the supervised learning strategy of ANNs to develop the controller. In such an approach, an ANN is trained to behave like a specific form of a conventional controller. Input and target data are generated from the input and output of that controller when operating in a normal closed loop fashion in conjuction with the plant. By using this approach, we first designed two PID controllers at a speed of 4.2m/sec and 8.4,/sec and then used these controllers as supervisors of the RBF controller in the training phase. The main purpose was to develop a single RBF controller, that yields satisfactory performance at speeds from 4.2m/sec to 8.4m/sec and even outside this range of speeds. As already mentioned, the OLS algorithm was used to train the network. It was found that for an optimum choice of Gaussian activation function width the controller performs well from a speed of 4.2m/sec. to at least 15m/sec

To develop the LMN, we used the structure of Figure 2 with two local models. These models were the two Nomoto's models derived at 5m/sec. and 10m/sec. The Gaussian functions with centres at the above speeds were chosen as the activation functions. Extensive simulation studies revealed that the LMN could provide exactly the same behaviour as is obtained by the conventional ship model (equation (1)). Due to space limitations, only a few simulation results are illustrated in Figure 3 and Figure 4. The success of RBF controller as well as well as LMN is quite obvious from these figures.

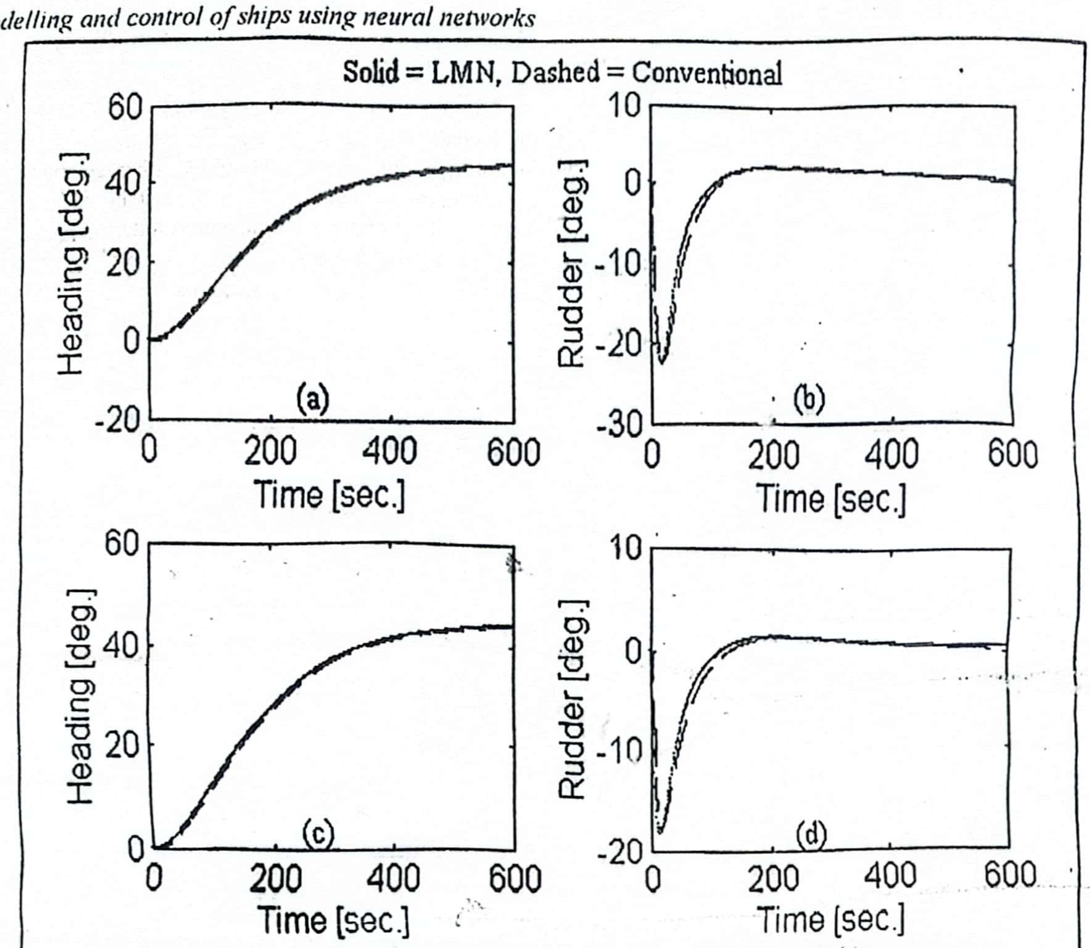

Figure 4 (a) Heading response at 7 m/sec (b) the corresponding rudder response
(c) Heading response at 9 m/sec (d) the corresponding rudder response

Conclusion:

In this paper we have investigated the applicability of artificial neural networks to both modelling as well as control of a ship. An RBF controller is trained successfully and it yields satisfactory performance at varying speeds of the ship, though its weights and biases are fixed. For modelling the ship dynamics, a special form of RBFNs, known as LMN has been used. It is demonstrated that the [illegible]del [illegible] like conventional ship models.

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