IDENTIFICATION OF MINESNIPER'S DAMPING PARAMETERS USING NEURAL NETWORKS

Experimental Results

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Abstract: In this article experimental work is presented on the identification of the damping parameters in a new defence system, called Minesniper. Simulations have revealed that the standard identification model for the damping parameters with a linear and a quadratic term yields inaccurate results. Therefore, neural networks are used to represent the damping. As the available, noisy training data set is too short for a full identification of the dynamics, feedback neural networks encounter problems in representing the damping in regions that have not been visited during training. To alleviate this problem radial basis functions have been applied successfully.

Keywords:

Autonomous vehicles, Backpropagation, Marine systems, Neural networks, Nonlinear systems, Radial basis function networks, System identification

1. INTRODUCTION

The Minesniper is a torpedo shaped underwater craft used for finding and detonating sea mines in a controlled way. Currently the Minesniper, which is shown in figure 1, is in its final stage of development and testing. To improve control of the craft, non-linear controllers and observers are being designed.

The model of the Minesniper used for simulations was derived using standard techniques and software such as WAMIT (Refsnes, 2003). For slender

bodies, such as the Minesniper, these techniques generally give good results for the mass and added mass matrices. However, for the damping, the parameters obtained from hydrodynamic computations, are at best a reasonable approximation (Refsnes and Sørensen, 2004). Whereas potential damping can be calculated accurately, other contributors to the damping, such as skin friction, are not determined easily. The inaccuracies in the damping estimates are illustrated in figure 2, in which both the measured trajectory and a trajectory obtained from simulations with the

Fig. 1. The Minesniper MK II, courtesy of Kongsberg ASA

model based on (hydrodynamic) computations, are shown. In this model, linear and quadratic damping are modelled. Dots are placed on the tracks every second to indicate time in this figure.

Fig. 2. Measured trajectory (dotted line) of the MineSniper in a horizontal plane and trajectory predicted with a model based on (hydrodynamic) computations (solid line)

To improve the modelling of the damping, neural networks are used in an identification scheme as outlined in Van de Ven *et al.* (2004). Based on the real acceleration, $\dot{\nu}_{ppm}$, and the acceleration obtained from a control plant model, $\dot{\nu}_{cpm}$, in which the exact mass, $\mathbf{M}$, and input forces are known, but the damping, $\mathbf{D}$, is regarded to be zero, the product of damping and velocity, ν^1 , is obtained for all velocities at which the craft travels during the experiments:

$$\mathbf{D}(\nu) \nu = \mathbf{M} [\dot{\nu}_{cpm} - \dot{\nu}_{ppm}]. \quad (1)$$

Consecutively six separate neural networks are trained to each represent one element of the six element vector, $\mathbf{D}(\nu) \nu$. As the inputs to the neural networks are the velocity of the craft, the neural networks are trained to perform a

mapping from ν to $\mathbf{D}(\nu) \nu$. After training the neural networks can be used in the model as shown in equation 2:

$$\mathbf{M}\dot{\nu} + \mathbf{C}(\nu)\nu + \underline{\mathbf{D}\nu} + \mathbf{g}(\eta) = \tau, \quad (2)$$

where $\mathbf{C}$ is the Coriolis and centripetal forces and moments matrix, $\mathbf{g}(\eta)$ is the vector of restoring forces and τ is the vector of input forces. In equation 2, $\underline{\mathbf{D}\nu}$ is underlined to emphasise that this term is not a product of $\mathbf{D}$ and ν , but is the output of the neural networks. In Van de Ven *et al.* (2004) the identification of the damping was performed using back propagation neural networks. During the identification of damping in the Minesniper, however, it was found that insufficient information was available to train the neural networks for all possible velocities in all 6 degrees of freedom. If, during prediction of the craft behaviour, the neural network is presented with a velocity that is significantly different from those available in the training data set, the neural networks will have to rely on extrapolation to yield an estimate of the damping. For back propagation neural networks, the extrapolation behaviour is nonlinear and can thus yield unreliable predictions. This is highly undesirable as it may lead to instabilities of the model. Radial basis function (RBF) networks are used to prevent the unreliable predictions from occurring. In an RBF network the neurons are placed in an m -dimensional space, where m is the dimension of the input vector. The neurons are spread out over the m -dimensional space in such a way that the mean square error of predictions, measured over the full training set, is minimised (Chen *et al.*, 1991). An RBF network possesses the property of zero prediction when an input vector is presented that is new to the network. New in this sense means that the Euclidian distance between the presented input vector and the positions of all the nodes in the RBF network is larger than a pre-determined value. The prediction of the damping will thus in the worst case be zero.

As outlined in the previous, the Minesniper uses a sliding mass, m_b , comprising of the battery, to induce a pitch moment. As a result the dynamics model of the craft exhibits time-varying parameters that are normally constant. The mass matrix will become time dependent due to the changing position of the battery, $\mathbf{r}_b$, which in turn effects the Coriolis matrix. Due to the changing centre of gravity the vector of restoring forces will also show changes. Additionally it can be shown that the sliding pitch mass gives rise to an extra vector of forces and moments dependent on the velocity of the vehicle and the position and velocity of the sliding mass. In equation 3 this vector of forces and moments is written as a vector product of a matrix $\mathbf{V}$ with the velocity ν .

¹ The subscript ppm and cpm are dropped for ν as $\nu_{ppm} = \nu_{cpm}$

$$\mathbf{M}(\mathbf{r}_b)\dot{\boldsymbol{\nu}} + (\mathbf{C}(\boldsymbol{\nu}, \mathbf{r}_b) + \mathbf{D}(\boldsymbol{\nu}))\boldsymbol{\nu} + \mathbf{g}(\boldsymbol{\eta}, \mathbf{r}_b) + \mathbf{V}\boldsymbol{\nu} = \boldsymbol{\tau}, \quad (3)$$

with:

$$\mathbf{V} = \begin{bmatrix} 0^{3 \times 3} & -S(m_b \dot{\mathbf{r}}_b) \\ 0^{3 \times 3} & -2m_b \dot{\mathbf{r}}_b [\mathbf{r}_b + \mathbf{r}_g^b] + S(m_b \dot{\mathbf{r}}_b) S(\mathbf{r}_g^b) \end{bmatrix}, \quad (4)$$

in which the S operator is defined as in Fossen (1994). The changing position of the centre of gravity, $\mathbf{r}_g^b$, and its velocity, $\dot{\mathbf{r}}_g^b$, can be written as:

$$\mathbf{r}_g^b = \frac{m_1 \mathbf{r}_1 + m_2 \mathbf{r}_2 + \dots + m_n \mathbf{r}_n}{M} + \frac{m_b}{M} \mathbf{r}_b \quad (5)$$

$$\dot{\mathbf{r}}_g^b = \frac{m_b}{M} \dot{\mathbf{r}}_b, \quad (6)$$

where m_i $i \in 1, 2, \dots, n$ are all mass elements contained in the craft, apart from the battery mass and $\mathbf{r}_i$ $i \in 1, 2, \dots, n$ are their positions. $\dot{\mathbf{r}}_b$ is the velocity of the sliding battery mass and M is the total mass of the craft.

2. PRACTICAL RESULTS

The Minesniper MKII is torpedo shaped and is 1.93m long and 0.17m in diameter. Its weight is 40kg and it has a nominal speed of 3kn. Main propulsion is achieved using two 150W/24V DC electric motors located on each side of the hull at the center of the vehicle providing surge and yaw motion. In transit, pitch and thereby depth is controlled by movement of 1.7kg mass which is placed in the rear half of the vehicle. In addition, a 70W/24V DC vertical motor is placed at the center of the vehicle primarily intended for depth control in the vicinity of the target. With this actuator system, the vehicle is capable of controlling surge, heave, pitch and yaw.

Using the derived model (equation 3), the input forces from the thrusters and sliding pitch mass were calculated for the test runs. During these runs the position and attitude of the craft was measured and recorded using a short base line acoustical position measurement system. After post processing of the position data to obtain smooth signals, the velocity and acceleration of the craft were obtained through differentiation and transformation of the position data. This is admittedly a method prone to the introduction of large errors, but necessary given the fact that only position measurements were available. The obtained data was then used to calculate the training data for the neural networks as described by equation 1.

Fig. 3. Predicted (solid: original damping, dashed: RBF network damping) and measured (dotted line) trajectories of the Minesniper in a horizontal plane.

RBF network training was performed with a total of 50 seconds of experimental data. 15 Seconds of experimental data was used in a test set to validate the training results. The RBF networks each consist of 600 neurons. As, in RBF networks, the size of the hidden layer depends on the amount of information that has to be represented by the network, it can be expected that the amount of neurons necessary for identification of the damping for a full data set will increase substantially.

Figure 3 shows results of the RBF network training on the training data set.

As can be seen from figure 3, the RBF network models the damping accurately resulting in a correct prediction of the position up to 10 seconds into the simulation.

Performance of the RBF networks on the test data set is shown in figure 4. As the test set contains a high amount of not previously seen data, the original classical model of the damping is used in parallel to the RBF networks. The classical model represents the damping with a linear and a quadratic term as shown in equation 7:

$$\mathbf{D} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 83 & 0 & 0 & 0 & -20 \\ 0 & 0 & 85 & 0 & 30 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 27 & 0 & 9.5 & 0 \\ 0 & -17 & 0 & 0 & 0 & 6.8000 \end{bmatrix} + \text{diag}([7 \ 100 \ 250 \ 50 \ 90 \ 90]) \cdot \text{diag}(|\boldsymbol{\nu}|). \quad (7)$$

In case an input vector is presented to the RBF networks, that is significantly different from all input vectors used for training, the model will choose the output of the classical damping model rather than the output of the RBF networks.

Fig. 4. Predicted (solid original damping, dashed RBF network damping) and measured (dotted line) trajectories of the Minesniper in a horizontal plane.

As can be seen from figure 4, the RBF networks do not succeed to predict the position of the craft very accurately. However, this was not expected as the test data set is considerably different from the training data set. It can be seen though, that the prediction is more accurate than the prediction done by modelling the damping according to equation 7.

To gain insight in the damping representation learned by the RBF networks, estimates of the diagonal terms of this representation are distilled from the RBF networks using a least squares algorithm. First, by presenting the full training data set to the network, all values for the damping forces are obtained. Then, using the least squares algorithm, the optimum fit to a model for the damping, with a linear and a quadratic term, is distilled from the damping representation contained in the RBF network. The approximations of the diagonal elements of the damping forces, τ_D , as a function of ν and $|\nu|$ thus obtained, $\tau_D = f(\nu, \nu \cdot |\nu|)$, are shown in figure 5.

For comparison the same plots were generated for the diagonal damping parameters used in the classical damping model. The results are depicted in figure 6.

Comparison of figures 5 and 6 shows that the damping estimates in surge, sway, heave and yaw obtained with the RBF networks are physically plausible. The negative slope for higher sway and heave velocity may be due to the insufficient size of the data set that was available. However, this requires further research. For both roll and pitch the found values are physically impossible. From the plots a negative damping should be concluded for the regions around zero velocity. However, the

Fig. 5. Approximates of damping, as modelled by the RBF networks, in 6 degrees of freedom as a function of speed in the same degree of freedom.

Fig. 6. Approximates of damping, as modelled in the classical model, in 6 degrees of freedom as a function of speed in the same degree of freedom.

amplitude of the excitation in these degrees of freedom is too low to obtain reliable results.

3. CONCLUSIONS

In this article modeling of the damping of an underwater vehicle using radial basis function networks was discussed. Neural networks are used for the identification of the damping as they can represent the damping without using an explicit model. Rather than using back propagation neural networks, RBF networks were used as they have the convenient property that their output tends to zero for inputs different from the ones that were used for training. To improve the prediction of damping for these new velocities, a classical damping model is used in parallel to the RBF networks.

Results using experimental data were presented, showing the advantages of the presented modeling scheme. Other than for open loop predictions of the position, the model could function as an improved model in model predictive control.

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