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# SHIP MOTION PREDICTION FOR RECOVERY OF HELICOPTERS

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**Abstract:** Due to the random nature of the ship's motion in an open water environment, the deployment and the landing of helicopters from a ship can often be difficult and even dangerous. The ability to reliably predict the ship motion will allow improvements in safety on board ships and facilitate more accurate deployment of helicopters off ships. This paper presents an investigation into the application of artificial neural networks trained using singular value decomposition and conjugate gradient algorithms for the prediction of ship motion. This paper presents the results of the application of Artificial Neural Network (ANN) methods for the prediction of ship motion. Other requirements were that the methodology had to be close to real time and independent of ship characteristics so it can be easily implemented on different types of surface vessels.

## 1 INTRODUCTION

The ability to predict ship motion reliably in any sea state will support the operations of air vehicles off ship platforms as shown on Figure 1. For example, the landing and take off of helicopters, whether manned or unmanned, from ship decks in rough sea conditions can be difficult and dangerous. The critical factor in these operations is that there is usually a delay between the moment the decision is taken to launch or recover the helicopter and the actual moment this operation takes place. This means that the ship motion and attitude can change for better or for worse.


*Figure 1 : Helicopter ship landing.*

Pilots currently make use of pre-computed operational envelopes listing the conditions for landing of many ship-rotorcraft combinations [1]. The envelope conveys a go/no-go decision to the pilot. With future ship motion data communicated in real time it may be possible to extend the envelope.

If the motion of a ship can be predicted with reasonable accuracy and communicated to the aircraft or helicopter, touchdown dispersion can be improved upon while landing or a smoother aircraft trajectory can be achieved on take off, either by anticipating the ship motion or by delaying the operation until conditions improve. Besides improving safety, reducing the touchdown dispersions also reduces landing and takeoff loads, which in turn increases the life of the airframe and reduces maintenance and repair cost.

There is a demand on helicopter pilots to be highly skilful and this is especially necessary when the pilot must land on a moving helicopter deck on a floating vessel [2]. The issue of helicopter of helicopter ship landing has been a long standing problem and the Navy has long operated a program to perform flight testing in this environment with the stated goal of improving flight safety [3]. There are a number of variables that must be considered when the pilot is landing and launching his aircraft. Many of these factors cannot be controlled as they are influenced significantly by the environmental elements.

An increasing percentage of helicopter accidents are being attributed to dynamic rollover, a phenomenon that will, without immediate corrective action, result in destruction of the helicopter and possible serious injury. The phenomenon of dynamic rollover is most likely to occur when the pilot of the helicopter is attempting a landing or take off when the ship is pitching or rolling.


*Figure 2: Example of the upslope rolling motion.*

Figure 2 shows a diagram depicting the situation where dynamic roll over may occur. The pilot must be careful in making certain that the roll rates remain small. The pilot would need to slowly raise the downslope skid/wheel to bring the helicopter level and then lift off. If landing, the pilot would need to land on one skid/wheel and slowly lower the downslope skid/wheel using combined movements of cyclic and collective.

If the helicopter rolls to the upslope side (approximately 5° to 8°), the pilot should decrease collective (the control used to control the pitch of the main rotor blades) to correct the bank angle and return to level attitude and then start the landing procedure again. Dynamic rollover can occur in either the skid or wheel equipped helicopter. All types of rotor systems, rigid, semi-rigid, or fully articulated are affected to some extent. Tail rotor thrust and wind drag on the fuselage contributes to the roll moment.

"The insidious aspect of dynamic rollover is that the roll rates which precipitate it are within the range the pilot would normally allow in flight" [4]. Therefore a helicopter could be placed in a rollover situation well before the pilot recognizes it. This makes it necessary to ensure that the pilot has enough information about all of the major factors which can adversely affect the safety of the helicopter.

Another important consideration when landing a helicopter on a ship platform is the deck energy level. The deck energy level of the landing area on a ship is a critical factor for a helicopter pilot when attempting to land the aircraft on the ship platform. If the energy level of the deck is too high, the pilot may damage the structure of the helicopter due to the impact of landing [5]. Even if the structure is not completely destroyed, repeated impacts on the structure will lead to the eventual failure of the structure in time [6]. If the helicopter structure is damaged the cost to the operator could be in the millions of dollars or the helicopter may be lost altogether. The impact of the landing can be reduced by choosing a period of time where the deck energy levels are low and there is a smaller chance of hard impacts with future ship motion data relating to the vessel's deck energy levels.

The more information available, the better the chance that hazardous situations are identified which improves the opportunity to take the necessary preventive measures to avoid disaster. It is envisaged that the future ship motion can be calculated and communicated to the pilot in real time. For example, a landing period designator could be developed that predicted the future ship roll and pitch motion as well as the deck energy level. In difficult situations this data could be communicated to the pilot to inform him when it is safe to land.

## 2 ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) form a class of systems that are inspired by biological neural networks [7]. A neural network is simply a series of neurons that are interconnected to create a network. They are a class of non-linear systems and there are a wide variety of different approaches that can be used.

The use of ANN in time series prediction relate to the application of ANN for the nonlinear system identification. The use of ANN is particularly appealing due to the ability of the ANN to learn and adapt which will be important for this investigation as one of the underlying goals is to create an algorithm that is able to work in all conditions and environments.

The ANN architecture that will be used to create the ANN for time series prediction will be the multi-layer feed-forward ANN. This type of architecture has a minimum of two layers consisting of the input layer and the output layer. In this investigation a three layered feed forward neural network consisting of an input layer, a hidden layer and an output layer is used. In a feed-forward ANN the inputs for each layer come from the preceding layer. A single neuron is shown in Figure 3.

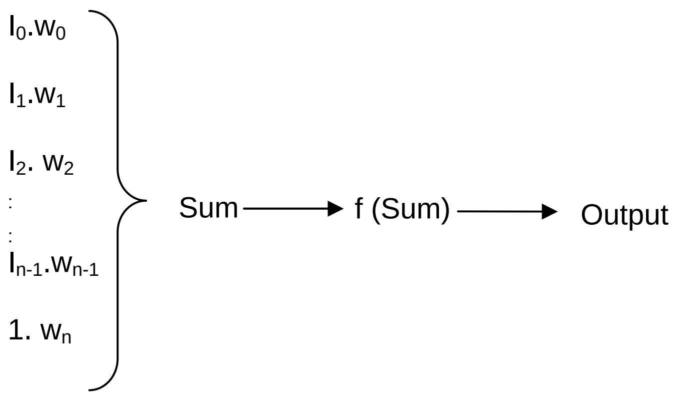


*Figure 3 : A representation of a single neuron.*

It has n inputs including a bias term, which has been set to 1. The inputs are each multiplied by their corresponding weight value summed together and subsequently entered into an activation function. The output of the activation function will correspond to the output of the neuron.

Mathematically, the output of a neuron is given as

$$out = f\left(net\right) = f\left(\sum_{i=0}^{n-1} x_i w_i + w_n\right) \tag{1}$$

where the inputs are $\{x_i, i = 0,...,n-1\}$. Generally the neuron's operation is not affected significantly by the activation function but the training speed is affected somewhat [8]. The activation function is usually a non-linear function that determines the output of the neuron. Its domain is generally all real numbers. The range of the output for an activation function is usually limited between 0 to 1 and sometimes –1 to 1. The majority of activation functions use a sigmoid (S-shaped) function because it is differentiable. According to Masters [8] any continuous, real valued function whose domain is the set of real numbers, whose derivative is always positive and whose range is bounded can be approximated using a three-layered feed-forward ANN.

In this investigation the *hyperbolic tangent* and (scaled) *arctangent* is used:

$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{2}$$

In summary, a three-layer network is all that should be required for any function that is continuous. If there are discontinuities then more than one hidden layer may be required. The most important characteristic of a correctly designed multi-layer feed-forward network is that theoretically it can learn to approximate any continuous function.

### 2.1 Beneficial features of the ANN for ship motion prediction

The use of ANN for time series prediction has a number of distinct advantages. Firstly, any amount of information pertinent to the prediction can be incorporated into the ANN. There is also no need to choose any particular model for the ANN. A validation process is included to ensure that the ANN is working correctly. It is to ensure that the ANN has not over-fitted the data. If the architecture of the ANN is poorly designed, the ANN may be able to learn irrelevant details specific to the training set which will lead to an ANN that is only relevant to the training set. Conversely, the ANN may have a deficient architecture where the ANN is not able to learn the subtleties required for accurate outputs. The validation process should reveal these problems.

### 2.2 Training the Network

The training of the network can be viewed as a minimization process where the weights in the ANN are systematically adjusted in a manner that reduces the error between the output of the ANN and the desired output. Therefore the process of training the neural network becomes an optimization problem where the performance of the neural network will be dependent upon the quality of the solution found after the training process has been completed.

The aim of this investigation is to develop a methodology to predict ship motion in real time. Singular value decomposition (SVD) is a linear regression technique that can quickly obtain an approximate set of optimum weights which is far superior to randomly generating the weights. A detailed description of the SVD technique is beyond the scope of this paper but essentially the matrix $X$ which satisfies the function:

$$A.X = B \tag{3}$$

when $A$ and $B$ are known can be calculated efficiently using SVD. When applying it to the ANN process the weights between the input layer and the hidden layer are initially randomly generated. The training samples are then inserted into the ANN and the hidden layer activation functions are calculated creating a matrix equivalent to $A$. Also, the values for the inverse transfer function of the output are also calculated creating a matrix equivalent to $B$. Applying SVD and solving equation (3), the approximate optimal weights $X$ are found.

The conjugate gradient (CG) algorithm created for the ANN in this investigation was based on the Polak-Ribiere algorithm and is used with the SVD method. The mathematical justifications for the algorithm are beyond the scope of this paper but a detailed description can be found in Polak[9]. In a general sense, the algorithm generates a sequence of vectors and search directions. It can be shown that the exact minimum will be obtained if the multi-dimensional function can be expressed as a quadratic. The ANN error function is quadratic close to the minimum so it is expected that once close to a minimum, convergence to the local minimum will be very rapid [10]. Therefore the best values returned from running the SVD can be used as the initial starting point for the conjugate gradient search.

### 2.3 Validation of ANN Model

To ensure that the weights in the ANN have been correctly set and that the output of the ANN is sufficiently reliable, a validation process is applied after training has been completed. The set of known inputs with their desired output needs to be divided into two distinct sets. The first set is the training set and is used throughout the training period to adjust the weights to the appropriate values. The second set is referred to as the validation set and is used to test the ANN. Once the values of the training set have been determined, the inputs from the validation set are inserted into the ANN and the output of ANN is compared with the target values in the validation set. The validation process is included to ensure that the ANN is working correctly. It is to ensure that the ANN has not over fitted the data.

The architecture of the ANN refers to the number of neurons that are used in the input and hidden layers. If the architecture of the ANN is poorly designed, the ANN may be able to learn irrelevant details specific to the training set which will lead to an ANN that is only relevant to the training set. Conversely, the ANN may have a deficient architecture where the ANN is not able to learn the subtleties required for accurate outputs. The validation process should reveal these problems. The entire ANN process including the validation process is shown in Figure 4.

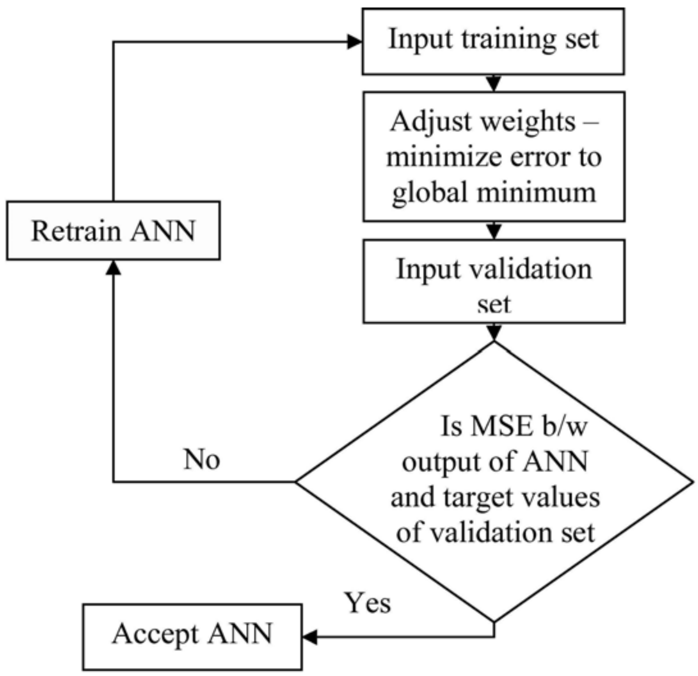


*Figure 4 : The artificial neural network process.*

It can be clearly seen that the first stage involves inputting the training set into the ANN. The ANN adjusts its weights in the 'learning' process until the error between the target values and the output of the ANN is reduced to a minimum. Next, the validation set is inputted into the ANN. The output of the ANN is compared to the target values of the validation set and the

ANN is accepted if the error is of a low enough value or alternatively rejected if the error is too high.

The error in the validation set may be higher than the error found at the end of training but should not be significantly larger or there is a problem with the ANN. Also, the validation set should be independent to the training set to ensure that there is no bias added into the validation process. It is not permissible to use any of the training data in the validation stage, as this will not give a good indication of the ANN's validity.

## 3 RESULTS

The algorithm developed were subsequently applied to measured ship roll angle data taken from a cruiser size vessel operating in sea states 5-6. The term sea state is a description of the properties of sea surface waves at a given time and place [11]. The greater the sea state the rougher the conditions. The results shown in this section are the average results obtained by applying the algorithm to four separate ship motion databases. Each database had approximately 600 seconds of roll angle data available sampled at 2Hz. The training data was set to two thirds of the data sets and the validation set was designated as the final third of the data sets. All results shown in this section are the predictions made using the validation set only. A graphical representation of the results is shown in Figure 5 while an example prediction is shown in Figure 6.

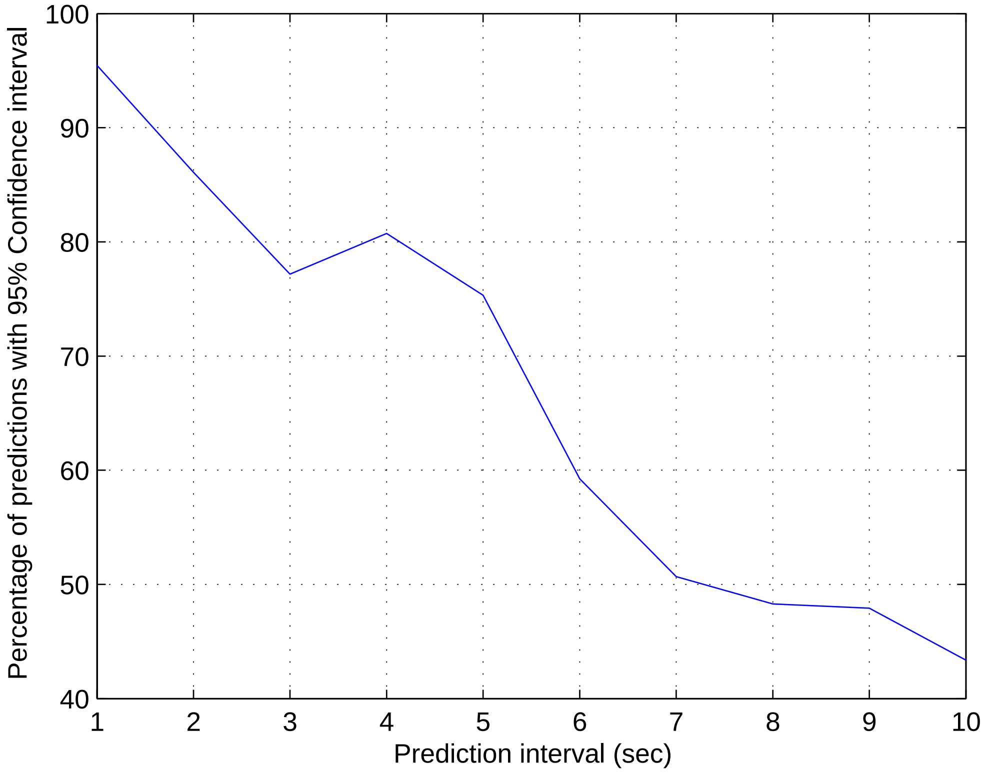


*Figure 5: Prediction of roll motion (frigate class ship in sea state 5-6).*

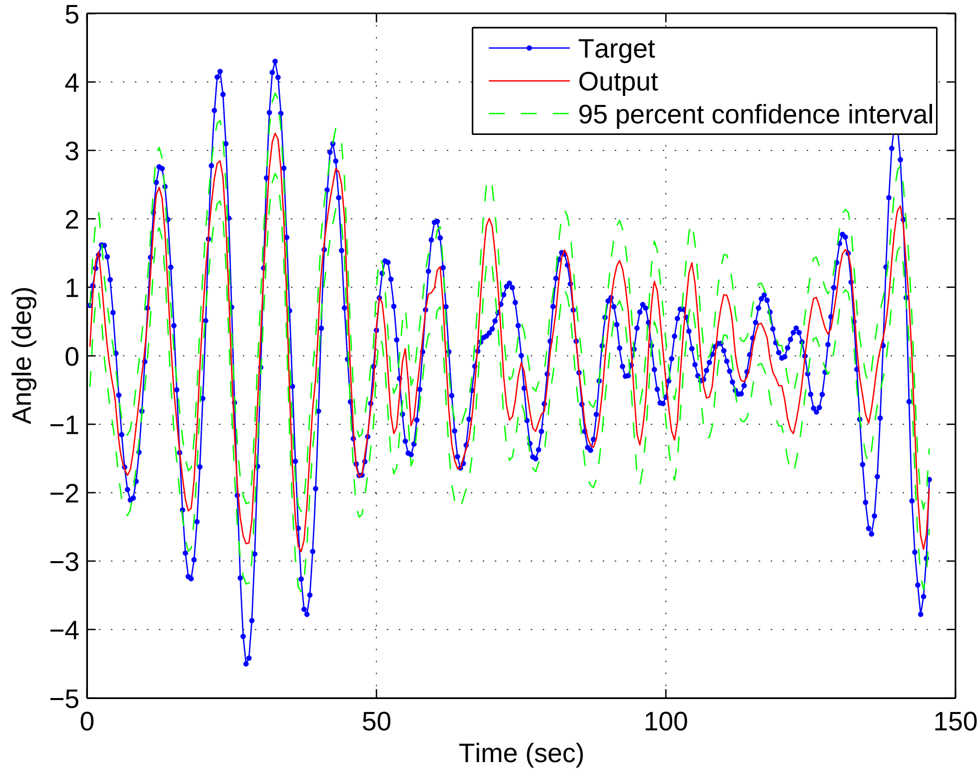


*Figure 6: Sample 10 second in advance prediction generated using the ANN algorithm with 8 neurons in the input layer and 3 neurons in the hidden layer.*

In this investigation the ANN had eight neurons in the input layer and three neurons in the hidden layer. The output layer naturally only had one neuron. Therefore, for every lead prediction interval a single ANN is used. The ANN is capable of creating multiple predictions of different magnitude but it is better that a separate ANN is used for every prediction interval. The basis for the presumption is that the weights for an optimal prediction will vary according to the prediction interval desired. By having the ANN create multiple predictions, the overall optimal prediction cannot be made. By having separate ANN create separate predictions, the optimal weight configuration can be obtained for each prediction and therefore, higher accuracy can be expected.

During the training process thirty separate trials were conducted using the SVD training algorithm and then the best solution was chosen and inserted into the CG algorithm as the initial starting point for the CG search.

Figure 5 shows that at low prediction intervals the accuracy levels are extremely high and the quality of the predictions reduces as the prediction interval is increased. This is as expected.

One of the anomalies that can be seen in Figure 5 is that the 4 second prediction is better than the 3 second prediction. The explanation for this anomaly relates to the operation of the SVD algorithm. As stated in section 2.2, when applying the SVD to the ANN process, the weights between the input layer and the hidden layer are initially randomly generated. Therefore the ANN was able to produce exceptionally high levels of accuracy for one of the databases because it had a very good set of randomly generated weights and therefore the overall average was very high. To ensure that the ANN has the best set of initial weights it would be necessary to conduct as many trials as possible of the SVD. Each trial would have a unique set of input weights and potentially lead to better overall accuracy. However, there is an associated cost in the form of computational processing time.

It can be clearly seen in Figure 5 that the accuracy level when the prediction interval is ten seconds is approximately 40%. This may seem quite poor but if Figure 6 is examined it is evident that the ship motion is still very well represented. The important aspect that should be considered with regards to Figure 6 is that the large fluctuations in the amplitude of the motion are well represented. The ANN was also able to predict the region of motion where the amplitude is not large which is equally important. For example, if one wanted to land a helicopter on a ship deck the pilot would be interested to know when the roll motion would have a large amplitude as this would make it unsafe to land, but equally important is knowing when the amplitude is low as this would mean that it would be safer to land. Therefore the algorithm is capable of predicting the periods in time in which the motion amplitudes are low and high. The prediction interval is as high as 10 seconds. This shows that using the ANN algorithm trained using a combination of the SVD and CG algorithms is very effective

## 4 CONCLUSION

In this paper an artificial neural network based method utilizing a combination of the singular value decomposition and conjugate gradient algorithm for the prediction of the ship motion was presented. It was shown that the artificial neural networks were capable of learning the motion and producing accurate predictions for intervals up to 10 seconds. The most important outcome of the investigation was that the high and low amplitude motion was very well represented for all prediction interval lengths.

## 5 ACKNOWLEDGMENTS

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