

# Hull Deformation Estimation Based on Neural Network

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## **Abstract:**

Hull deformation is an important factor affecting the consistency of ship attitude. Hull deformation measurement methods, such as optical measurement method, inertial matching measurement method, etc., can accurately measure the hull deformation. However, these measurement methods require the installation of deformation measurement equipment at the location where the deformation is measured, which limits the deformation measurement method to be used on large ships with numerous onboard equipment. In this paper, a ship deformation estimation technology based on neural network is proposed, analyzes the ship deformation transfer law, builds the ship deformation estimation neural network model, and estimates the deformation information of adjacent positions through the deformation information of the known position, so as to obtain the whole ship deformation information, and the attitude of the whole ship can be achieved. Finally, the experiment is carried out on a ship model, the relative deformation data of different positions and multiple directions are collected, the neural network model is trained, and the model is verified with the test data. The results prove the feasibility of estimating ship deformation transfer based on neural network.

**Keywords:** hull deformation; Neural network; Consistent posture; Deformation estimation; Attitude compensation.

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## I. INTRODUCTION

Under the influence of environmental factors such as load changes, weapon impact, wave impact, and sunlight, temperature, and other environmental factors, the hull deformation of the ship will occur [1]. Hull deformation will cause coordinate misalignment between the coordinate system of radar, weapons and other shipborne equipment and the reference coordinate system of the main inertial navigation (MINS), which will affect the ship's attitude unity and lead to the decrease of detection, tracking and strike accuracy or even failure [2-3]. Fig 1 shows an example of a deformable ship resulting in a decrease in weapon strike accuracy. In order to eliminate the influence of the hull deformation on the uniform attitude of the ship, there are various methods for measuring and compensating the hull deformation such as optical measurement, local reference method and inertial matching measurement [4-5], which can basically meet the requirements in measuring the hull deformation accuracy [6]. but the optical measurement method requires the arrangement of large-scale equipment, and requires two points to be able to view together [7],

the local reference method and the inertial matching measurement method require the arrangement of expensive inertial navigation [8], these shortcomings limit the extensive use of deformation measurement technology in practical engineering is especially not suitable for large ships with many shipboard equipment and large dimensions. Therefore, a deformation estimation method that does not depend on equipment layout is urgently needed.

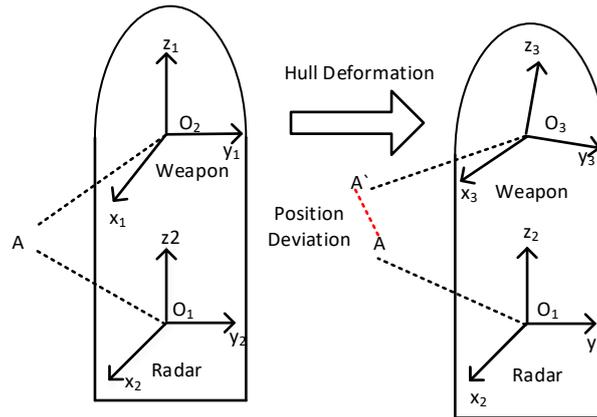


Fig 1: Hull deformation affects weapon strike accuracy

The ship hull deformation transfer law is determined by the mechanical structure of the ship itself, but it is very difficult to accurately describe the mechanical structure of the ship by mathematical analysis method, so many researches use elastic mechanics theory to study the ship hull deformation transfer law, and simplify the ship into Bernoulli beam [9], but the simplification of hull model will introduce relatively large error, resulting in the low accuracy of this method; Some scholars use finite element analysis to analyze ship hull deformation [10], which improves the accuracy of hull deformation calculation, however, the lack of real-time ability and inability to deal with hull deformation caused by complex stress limit the application of finite element analysis in hull deformation transfer. Some scholars use stochastic process to describe ship deformation model, such as second-order Markov process to describe ship dynamic deformation [11], and the random walk model to describes the static deformation of ships. This method can fit the deformation of the ship in a short period of time. However, it will encounter the problem of not being able to handle long-term non-convergence, which contradicts the limited deformation of the ship. In summary, although the above methods can describe the deformation transfer characteristics of ships under certain circumstances, they have various shortcomings and cannot accurately fit the hull deformation law, which is mainly caused by the nonlinearity of the hull transfer law. Although the hull deformation can generally be analyzed by the hydroelastic model, due to the complex structure of the ship, there are many beams and longitudinal beams, which leads to the complexity and nonlinearity of the deformation transmission. The neural network has very good nonlinear fitting ability, so this paper proposes a ship deformation transfer technology based on neural network, which uses neural network simulation to fit the ship deformation transfer law, and estimates the deformation information of the unknown position according to the deformation information of the known position.

## II. DECK DEFORMATION ESTIMATION METHOD BASED ON GRID DIVISION

Ship deck is generally considered to conform to the assumptions of continuity, homogeneity, isotropy and small deformation in elasticity theory [12], From a spatial point of view, when a position is deformed due to external force, the deformation will be continuously transmitted to the surrounding position, driving the surrounding position to deform, and under the influence of internal force, it will continue to decay until it disappears. This transfer law is determined by the inherent properties of the ship deck material and the ship structure, and can remain stable under the condition that the environment changes little, so the neural network model can be used to fit this nonlinear change law. However, the neural network model can only fit the discrete point-to-point transfer relationship, and cannot fit a continuous analytical relationship, and the ship deck is a continuous area, which cannot be fitted by a neural network model.

In order to solve the above problems, the deck can be divided into grids, which only need to build a neural network model of several finite points on the grid intersection. For the positions not on the grid intersection, the deformation value can be calculated by interpolation, so as to obtain the deformation information of all positions on the ship deck.

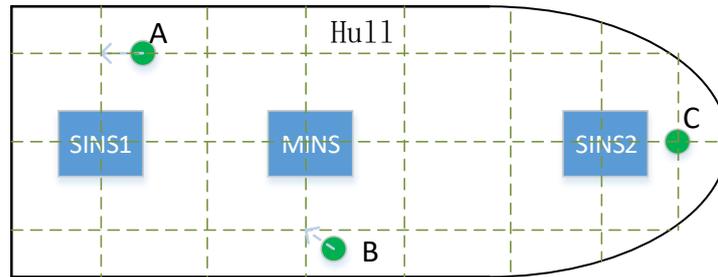


Fig 2: Deck area division

As shown in Fig 2, taking the main deck of a ship as an example, one main inertial navigation system (MINS) and two local inertial navigation systems(SINS) are arranged on the ship. There are three important positions A, B and C on the deck. To calculate the deformation information of these three positions, the deck is divided into grids, a neural network deformation estimation model is constructed at the grid intersections, and then the respective deformation information is calculated according to the deformation information at the nearby grid intersections. The calculation formula of the grid distance is as follows:

$$dist = l + \alpha m + \beta n \quad (1)$$

Where  $l$  is the straight-line distance from the point to be divided to the regional center;  $\alpha m$  and  $\beta n$  represent two constraint conditions respectively.  $m$  is the length of structures affecting deformation transmission, such as superstructure or hatch, between the point to be divided and the straight line of the center of the region, and  $\alpha$  is its weight factor;  $n$  is the number of strong support structures such as strong beam or deck girder in the same deck as the regional center at the point to be divided, and  $\beta$  is its weight factor.

After the division, the ship's main deck is divided into three grids centered on the INS. As shown in Fig 3, taking the region where position A is located as an example, the center of the region is SINS1. With the center of the region as the origin of coordinates O, the starboard direction is X-axis and the bow direction is Y-axis, the deformation transfer coordinate system of this region is established. At the same time, take a collection point every distance along the X-axis direction, and take a collection point every distance along the Y-axis direction, measure the deformation relative to the origin O at these collection points, and train the corresponding neural network model. To the non-collection point x, the deformation of this point can be obtained by spherical linear interpolation according to the deformation information of P1 and P2. The interpolation formula is as follows:

$$d(t) = k(t)(d_1 + t(d_2 - d_1))$$

$$k(t) = \frac{d_1}{d_1 + t(d_2 - d_1)} \quad (2)$$

Where,  $d_1$  and  $d_2$  are the deformation of adjacent positions, and  $t$  is the distance.

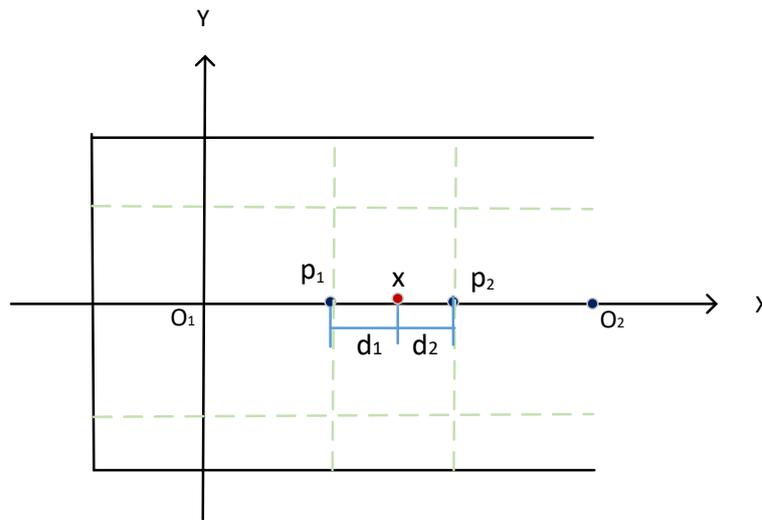


Fig 3: Calculated deformation inside the grid

### III. DEFORMATION TRANSFER MODEL BASED ON NEURAL NETWORK

When a position A is deformed, the deformation will be transmitted to the periphery, and the transmission law is affected by the structure and material of the ship, especially determined by the natural vibration frequency of the ship deck. In the case of fixed materials, the natural vibration frequency of the ship deck is mainly determined by the length of the ship deck. The horizontal and vertical lengths of the ship deck are different, so the ship's deformation transmission will show different laws in the horizontal and vertical directions. Therefore, the magnitude of the deformation caused by another position B is not only related to the distance between positions A and B, but also to the relative orientation of A and B.

Relative bearing A and B can be decomposed into vertical and horizontal two component, so the deformation at position B is the superposition of the lateral propagation and vertical propagation of the deformation at position A, thus the input of the neural network model can be constructed as the deformation at position A and the distance and relative orientation of positions A and B. The mathematical expression is  $= (x_1, x_2, x_3, x_4, x_5)^T$ , where  $x_1, x_2, x_3$  is the deformation value of the three axial directions at position A,  $x_4$  is the distance between positions A and B, and  $x_5$  is the relative orientation of A and B, which can be simplified to longitudinal and heading.

As shown in Fig 4, the constructed neural network model adopts a 3-layer structure, there is only one hidden layer between the input layer and the output layer. In the Figure 4, there are 5 neurons in the input layer,  $m$  neurons in the hidden layer, and 3 neurons in the output layer. The input vector of the sample is  $x = (x_1, x_2, x_3, x_4, x_5)^T$ , the output vector of the hidden layer is  $o = (o_1, o_2, \dots, o_j, \dots, o_m)^T$ ,  $o_j$  is the output value of the  $j$  neuron in the hidden layer, and the output vector of the output layer is  $y = (y_1, y_2, y_3)^T$ ,  $d = (d_1, d_2, d_3)^T$  is the actual output vector of the sample data.  $V_{ij}$  represents the connection weight between the  $i$  node of the input layer and the  $j$  node of the hidden layer, and  $W_{jk}$  represents the connection weight between the  $j$  node of the hidden layer and the  $k$  node of the output layer;  $b_j$  represents the threshold of the  $j$  node of the hidden layer, and  $\theta_k$  represents the threshold of the  $k$  node of the hidden layer.

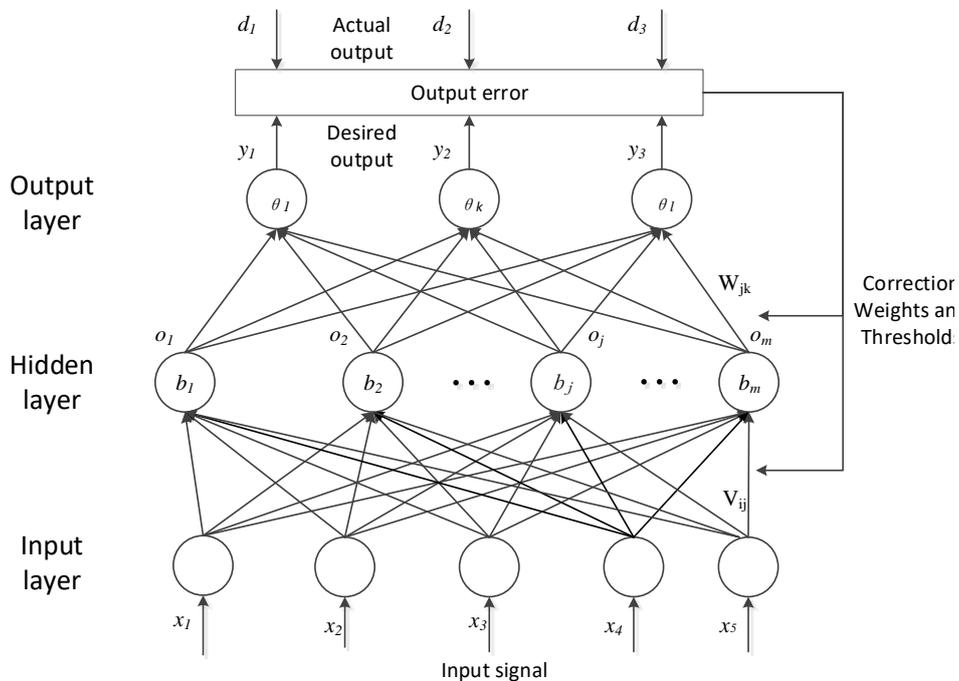


Fig 4: Structure of neural network model

## IV. EXPERIMENT AND DISCUSSION

### 4.1 Data collection

The key to training the neural network model lies in the data. In order to train the neural network model and verify the feasibility of using the neural network to fit the hull deformation transfer, this paper has carried out relevant experiments on a ship model. The shell plate of the ship model is made of 2mm thick Q345 plate, and the interior of the model is made of ordinary cold-rolled steel plate, with a total length of 26.82m and a width of 2.85m.

The relative deformation of the two positions was measured by the method based on inertial matching measurement with two type 90 laser INS, the accuracy of the deformation measurement was greater than 40 arc seconds for heading and greater than 20 arc seconds for pitch and roll. The two ins are fixed on the deck of the ship, and the layout is shown in Figure 5. The position of INS1 is not moved, and INS2 is arranged at a distance of 1m from INS 1 along the longitudinal direction and transverse direction respectively. The vertical impact is applied at the position of INS1, causing the hull deformation peak of about  $5^\circ$ , the impact frequency of 0.01Hz, and the deformation at position 2 measured at INS2. Four groups of data are collected from two directions. Each group takes one hour and contains about 700,000 pieces of data.

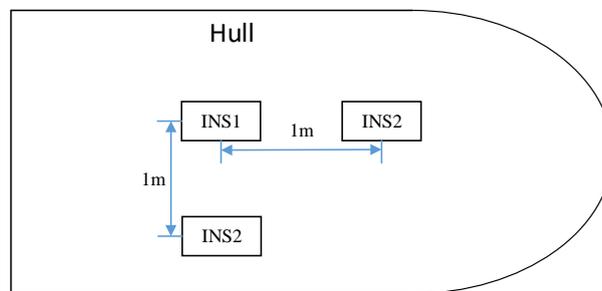


Fig 5: Deformation measurement

### 4.2. Neural network model training

The 8 groups of data collected are preprocessed to remove redundant data, and the data of inertial navigation 1 and inertial navigation 2 are aligned according to the time attribute. The final training data is shown in Table 1.

TABLE I . Training data set

Longitudinal direction	Group 1	Group 2	Group 3	Group 4
The data size	(7,707,748)	(7,681,833)	(7,677,174)	(7,712,493)
Transverse	Group 5	Group 6	Group 7	Group 8

direction				
The data size	(7,717,554)	(7,709,577)	(7,700,959)	(7,685,419)

Input the processed 8 sets of data into the neural network model respectively, take two-thirds of the data for training, and one-third of the data for testing. The number of model iterations is set to 2000, the learning rate is 0.005, the numbers of hidden layer neurons is set to 20, selects the ReLu function as activation function and the minimum mean square error as loss function, the neural network model is trained with each set of data, and the training loss of cutoff time model is shown in Table 2. It can be seen that the model trained with the first group of data in the longitudinal direction has the lowest loss, while that trained with the fifth group of data in the transverse direction has the lowest loss. The corresponding loss curve is shown in Fig6 and Fig 7.

**TABLE II. Final training loss of the model**

Longitudinal direction	Group 1	Group 2	Group 3	Group 4
Loss	0.029336	0.302557	0.03701	0.251746
Transverse direction	Group 5	Group 6	Group 7	Group 8
Loss	0.009879	0.214513	2.59609	2.613392

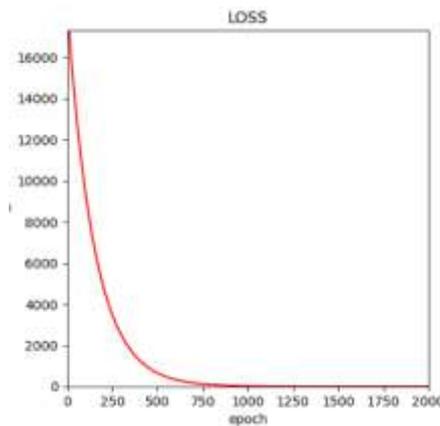


Fig 6: Training loss curve of group 1 data

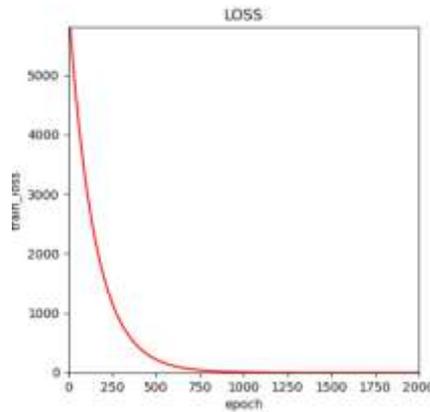


Fig 7: Training loss curve of group 5 data

In order to further test the fitting effect of the model on different data sets, the longitudinal and transverse data set models were cross-validated respectively to calculate the minimum mean square error (MSE) between the predicted value and the real value. The test results are shown in Table 3. It can be seen from the Table III that the deformation estimation accuracy of the longitudinal model is relatively high, indicating that at a distance of 1 meter, the neural network can better fit the longitudinal transfer of deformation, but the accuracy of the deformation estimation of the lateral model will be worse, mainly because the longitudinal length of the ship is much larger. this is mainly because the longitudinal length of the ship is much longer than the lateral length, which makes the lateral deformation transfer more complicated, so the use of a relatively simple three-layer neural network is not enough to fully fit the more complex lateral deformation transfer.

**TABLE III. Fitting effects of the model on different data sets**

Longitudinal direction		model			
		Group 1	Group 2	Group 3	Group 4
The data set	Group 1	0.0298	0.6975	0.091	0.6995
	Group 2	4.2605	3.6576	4.028	2.5648
	Group 3	0.0062	0.5497	0.0402	0.5497
	Group 4	4.9298	3.003	4.6578	3.5832
Transverse direction		model			
		Group 5	Group 6	Group 7	Group 8
The data set	Group 5	0.0098	0.4904	39.8264	232.2676
	Group 6	4.6721	3.6731	23.5318	186.5748
	Group 7	83.9394	73.0261	19.425	46.7158
	Group 8	300.9073	279.5268	125.9135	15.2403

## V. CONCLUSION

Due to the nonlinearity of the hull deformation transfer, this paper proposes a method of fitting the hull deformation transfer with neural network. The grid division method is used to divide the ship deck into limited key points, so that only the neural network model of key points needs to be constructed, and the deformation information of the entire ship can be obtained through interpolation calculation. The hull deformation transfer is decomposed into longitudinal and lateral components, a 3-layer neural network model with 5-dimensional input and 3-dimensional output is designed, and relevant experiments are carried out on a ship. The lateral and longitudinal neural network deformation transfer models with a distance of 1m are trained respectively, the results show that the deformation estimation accuracy in the longitudinal direction is high, and the maximum error is  $0.25^\circ$ , and the deformation estimation accuracy in the lateral direction is low, and the maximum error is  $2.6^\circ$ , this shows that the neural network can fit the deformation transfer of ships, especially for the fitting of longitudinal deformation transfer.

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