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Optimum Design of Ship Design System Using Neural Network Method in Initial Design of Hull Plate

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Manufacturing of complex surface plates in stern and stem is a major factor in cost of a preliminary ship design by computing process. If these hull plate parts are effectively classified, it helps to compute the processing cost and find the way to cut-down the processing cost. This paper presents a new method to classify surface plates effectively in the preliminary ship design using neural network. A neural-network-based ship hull plate classification program was developed and tested for the automatic classification of ship design. The input variables are regarded as Gaussian curvature distributions on the plate. Various applicable rules of network topology are applied in the ship design. In automation of hull plate classification, two different numbers of input variables are used. By observing the results of the proposed method, the effectiveness of the proposed method is discussed. As a result, high prediction rate was achieved in the ship design. Accordingly, to the initial design stage, the ship hull plate classification program can be used to predict the ship production cost. And the proposed method will contribute to reduce the production cost of ship.

Key Words : Ship Design, Optimum Design, Neural Network, Hull Plate, Artificial Intelligence, Automatic Classification

1. Introduction

Since a matter determined at the initial design stage affects widely the entire life cycle of ship, the initial stage of ship design is very important in the entire process of ship production. In the initial design, whole directions and qualities of design that include fundamental properties are decided and affect directly productivity in following construction work. In particular, it requires a broad knowledge of skilled designer to determine many elements for the generation of hull form. Recently, the design trend is interactive information flow rather than one-sided information flow. Accordingly, the efficiency improvement of initial design is a key role for raising the engineering technology of the shipyard in general. In the initial design, the main decision uses soft information. Soft information means the information that would be used at decision process, which is based on a judgment or an experience of designer. In the contrary, hard information means the information based on a scientific or engineering calculation. When design step and decision making proceed, the degrees of design freedom decrease and the knowledge of ship as a subject of design increase. Concurrently, the information used ot each design stage changes gradually from soft information to

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hard information. If a portion of hard information is raised at the initial stage of ship design, the whole design efficiency will be improved.

In general, there are several methods to raise a portion of hard information in the initial ship design. One of those is to use the existed data that had been accumulated and arranged for a long time. Design engineers who work for a shipyard have accumulated and arranged the data to utilize for past several decades. This data involve a ship designer's experience and design knowledge. If these data are utilized in ship design, it will be a great help in ship engineering. It can be said that the ship design is a process satisfying decision-based system. From this stand point, it is important how promptly and accurately those support in designers making decisions. At the initial stage, general directions of ship design are determined such for dimensions, hull form, and basic performance of a ship.

The main decisions of design which are made at the initial stages are based on the designer's own judgment and experience. These judgment and experience should be organized from the decision support system by using the artificial intelligence (Stuart and Peter, 1995).

There are various artificial intelligence techniques such as fuzzy logic, neural network and colony optimization, etc (Mamdani and Assilian, 1975). The artificial intelligence techniques are adopted in many research areas for generalization, pattern recognition, pattern classification and modeling of linguistic knowledge (Valluru and Hayagriva, 1993).

However, there have been little studies reported in ship design fields by applying artificial intelligence. Therefore, this study proposes a method by applying artificial intelligence to the preliminary ship design. A neural network as one of artificial intelligence technique is applied for the design technique (Rosenblatt, 1958 ; Shar and Palmieri, 1990). In order to apply artificial intelligence to the preliminary ship design, several cases which are typical ship design activities are tried to the initial stage.

On the other hand, the neural network can be learned by changing weights of individual input signals (Marenn et al., 1990). The neural network, which was once learned can memorize input data whether they have errors or is similar (Laurene, 1994). Therefore, the selection of input data that represent accurately the feature and exact objective patterns is an important point use of a neural network. Generally, the hull plates of ship can be classified into four types, in the flat, first surface, second surface and third surface according to the shape of curvature. The information of these plates distribution in the ship hull is an important factor in predicting of ship production costs. For input data in design, the geometric property of ship hull and classification results of a ship hull in accordance with experiences in a shipbuilding yard are adopted as objective patterns. Hwangbo et al. (2000) considered an angle in a ship hull at each point. Kim (1991) considered curvatures to represent the geometric property of a ship hull.

Nevertheless, the classification results using those geometric properties of ship hull could not show properly. It needs alternatives for more clear classification. Thus, Gaussian curvature distribution is considered for the geometric property in this study. The Gaussian curvature points are considered as input patterns. Then classification results are obtained as an objective pattern. This study investigated that the ship hull is possible to be classified effectively by applying the pattern classification to the ship design.

2. Modeling of the Ship Shope

Generally, the curvature of stern and stem of ship hull changes extremely. For the effective and exact modeling of such curvature of stern and stem, it requires a variety of topological surface patchs as well as rectangular patchs. For the proper expression of such curvature, Gregory patch is known as adequate surface for it (Choi, 1991). Gregory surface can be expressed with the rectangular curvature patch basically and with the non-rectangular curvature patch such as triangular or pentagonal patches. By applying the Gregory surface characteristics, a ship surface of tank carrier is modeled where the principal

Table 1 Principal dimension

Ship dimension	Type of ship	Tanker carrier
Length	L.O.A	271.000 m
Length	L.B.P	260.000 m
Breadth	(Moulded)	45.200 m
Depth	(Moulded)	20.200 m
Draft	(Designed)	15.100 m
Bilge	Radius	2.000 m

Fig. 1 The modeling of ship

Table 2 Classification of ship hull plates

Surface type	Criteria
Planar plane	No curvature in any direction, side and bottom plate of parallel mid body of ship
1st surface	Only one directional curvature Mainly press, roller bending machine
2nd surface	Only two directional curvatures, Line heating
3rd surface	Two directional curvature and torsion to one axis, bulb at a stem and stern among ship hull plate

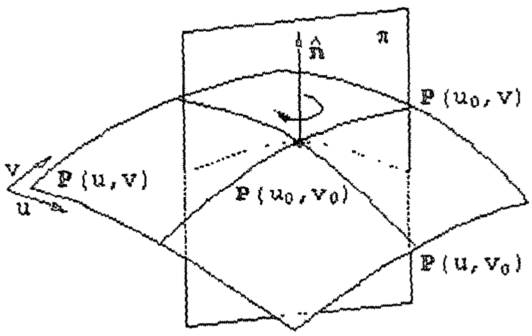


Fig. 2 Curvature of a parametric surface at plane P

dimension of the ship is described in Table 1. Fig. 1 shows a shape of the ship generated by the Gregory surface modeling. In table, the ship is a general tanker carrier. The length of all (L.O.A) is 271.000 m where the length between perpendiculars (L.B.P) is 260.000 m. The moulded breadth which does not contain the hull plate thickness is 45.200 m. The moulded depth which does not contain the hull plate thickness is 20.200 m. The designed draft of the ship is 15.100 m. The bilge radius in center of the ship is 2.000 m.

2.1 Methodology of ship hull modeling for classification

Currently in shipyard, the hull surfaces of ship are classified into planar plane, first surface, second surface and third surface according to the shape of surface and required manufacturing curvature. And the necessary surface processing works are divided into classes in their shapes, as classified in Table 2 by the experience of engineer.

The curvature of a parametric surface of plane is depicted in Fig. 2. By considering a planar plane π with a normal vector $\hat{n}$ of an arbitrary curved surface $P(u, v)$ at a point $P(u_0, v_0)$, a planar plane π revolves around a normal vector $\hat{n}$, and then an intersecting curve is generated between a curved surface $P(u, v)$ and a planar plane π, as shown in Fig. 1. This intersecting curve's shape on a surface $p(u, v)$ depends on a revolving direction of a planar plane π as explained in Fig. 2. According to a revolution of a planar plane, a curvature of an intersecting curve at a point $P(u_0, v_0)$ changes by rotation. And the maximum curvature and the minimum curvature are called the principal curvatures.

The Gaussian curvature at a point is the product of the maximum curvature multiplied by the minimum curvature. Also, the mean curvature is a mean of the sum of the maximum curvature and the minimum curvature. Thereby, those two values can be used as property characteristics values of local shape (Rogers and Adams, 1990). An arbitrary point on the curved surface can be classified according to the Gaussian curvature, as shown in Fig. 3. If a curvature on a surface is zero at all points, it can be said that this surface is developable. In other words, a surface like this can be laid out on the planar plane. Consequently, the Gaussian curvature can represent local property characteristics of a surface (Ye, 1994).

Table 3 Classification of surface type on the basis of the sign of the Gaussian and mean curvatures

		Gaussian Curvature		
		K<0	K=0	K>0
Mean Curvature	H<0	Hyperbolic point	Convex parabolic point	Convex elliptic point
	H=0	Hyperbolic point	Planar point	
	H>0	Hyperbolic point	Concave parabolic point	Concave elliptic point

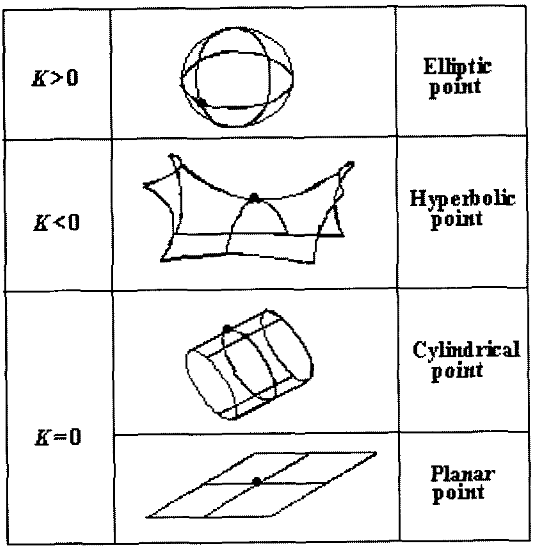
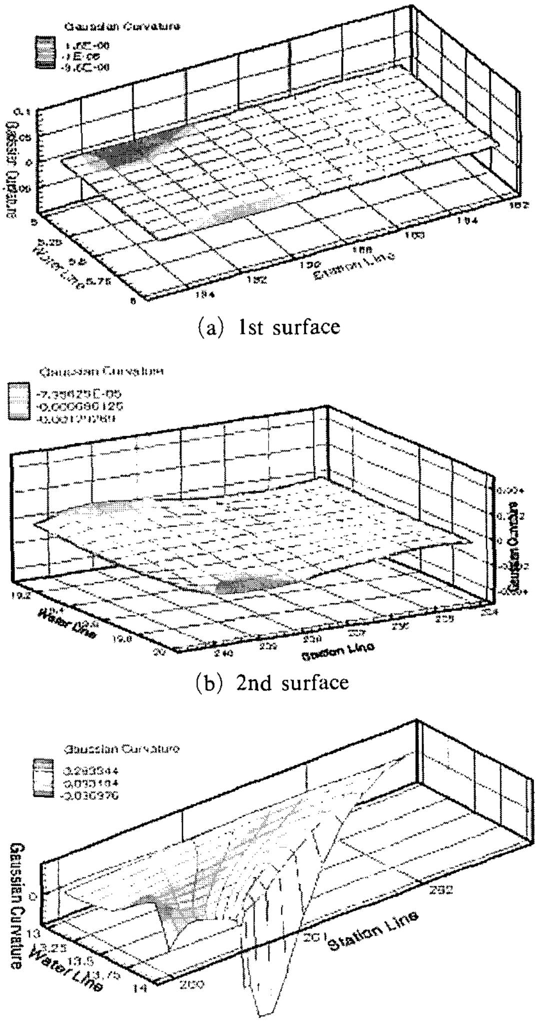


Fig. 3 Classification of surface points by the sign of Gaussian curvature

Correlations between Gaussian curvature and the mean curvature are described in Table 3. In table, **K** and **H** stand for the Gaussian curvature and mean curvatures, respectively. Classification of surface type in ship hull is carried out. The Gaussian curvature distributions are obtained, which corresponds to the shape of a typical first curved surface, second curved surface and third curved surface.

The Gaussian curvature distribution by the shape of a typical hull surface is represented in Fig. 3. Figures 4(a), (b), (c) show the Gaussian curvature distributions of a typical first, second and third surface, respectively. As can be observed easily from the figures, the Gaussian curvature is nearly zero in case of first surface. On the contrary, the Gaussian curvature have various values in case of second, third surface. Especially, in case of third surface, Gaussian curvature distribution is very complicated.



(a) 1st surface

(b) 2nd surface

(c) 3rd surface

Fig. 4 Gaussian curvature distributions of corresponding surface

2.2 Application of neural networks to automatic surface classification

The structure of neural network is shown in Fig. 5, which is applied to automatic classification of ship hull surface. In this neural network structure, unit neurons are connected to compose network each other (Freeman and Skapura, 1991). As described in Fig. 5, the connected cluster of neurons in horizontal is called layer. The neurons in the same layer perform the same work functionally, which become a basic unit of parallel and simultaneous action in neural network. Input layer receives data from outside and output layer generate data to outside. Hidden layer locates between input layer and output layer. In general, there has been no criterion to classify the various surfaces in shipyards. Moreover, it is hard to classify automatically the arbitrary surfaces.

In order to solve such classification problem, the pattern classification of neural network is applied in this study. In neural networks, training is accomplished by presenting a sequence of training patterns by changing the each weighted input pattern for the associated target against the repeated input data. Accordingly, an efficient neural network requires appropriate input patterns and target output patterns.

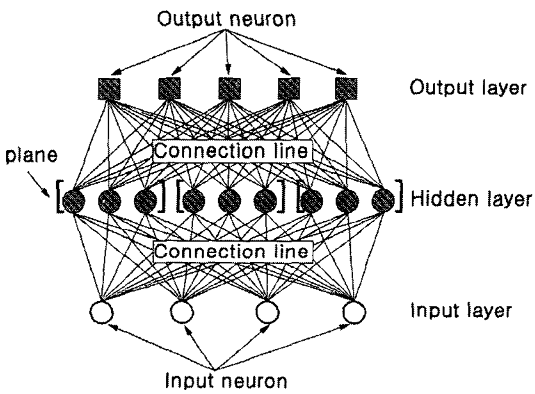


Fig. 5 Structure of neural network

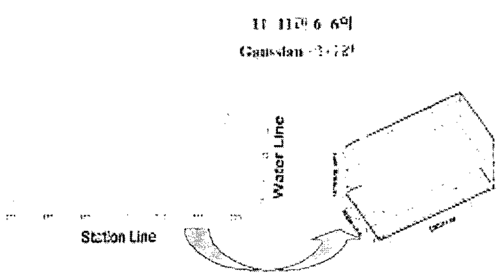


Fig. 6 Input patterns for neural network

In addition, the Gaussian curvature is used to deal with the shape of a hull surface in this study. It is effective to use the Gaussian curvatures of surface for input pattern and surface classification of ship design in shipyard. As input pattern, the surfaces are subdivided vaiformly in the length and width directions, as shown in Fig. 6. In other words, the total number of Gaussian curvature values is 36(6×6), and an which is divided into 5 intervals. And the total number of Gaussian curvature value is 121(11×11), which are divided into 10 intervals. Those values of Gaussian curvatures at the intersection points are used for input pattern, as shown in Fig. 6.

Target patterns use the result of classification of first, second and third surface based on the shell expansion. A neural network is to be trained with representative 11 training patterns which are obtained from first, second and third curved surface.

3. Result of Analysis Using the Neural Networks

3.1 Training result

An experiment is carried out to find which net architecture is most efficient in cases of change in input patterns and hidden layer. The properties of experiment for the design are described in Table 4. As described in table, three cases are considered in experiment, such as case 1, case 2 and case 3.

First different numbers of input variables are considered in case 1 where the hull is divided into 36(6×6) and 121(11×11). In second, different numbers of neurons with one hidden layer are considered in case 2 where the numbers of neurons of hidden layer are divided into 50 and 72. In third, different numbers of hidden layer are considered in case 3 where the numbers of hidden layer are divided into 1 and 2. The training is carried out in order to investigate how the number of hidden layer affects neural networks.

(A) Case 1

In this case, different numbers of input variables are considered. In other words, the input variables of the hull are divided into 36(6×6) and 121(11×11). At this time, the hidden layer is fixed as one. The training results of neural networks are described in Table 5 where the cycle stands for the training cycle. And the numbers of correct answers in training data are given below the 1st, 2nd and 3rd surfaces. When the training is carried out within the error 0.01 with 36 input variables and 50 neurons in hidden layer, the result is obtained in 31, 312 training cycles. And the neural network predicted the correct answers of the 1st, 2nd and 3rd curved surface as 11, 9, 11 numbers so that the correctness is 93.9%. It can be observed from the Table 5 that if the numbers of input variables are increased, then neural network perform becomes more efficient because more information is given to net architecture. Hence, the prediction rate becomes close to the correct one. And the training cycle for the prediction become smaller.

(B) Case 2

In this case, different neuron numbers of of hidden layer with one hidden layer are considered. Namely, the numbers of neurons of hidden layer are divided into 50 and 72. The training results of neural networks are described in Table 6. As can be observed in Table 6 that it doesn't affect the correct performance of neural networks in classification of hull, even if the numbers of neurons in hidden layer are increased. Nevertheless, the training cycle for the correct prediction rate becomes faster due to the increase of numbers

Table 4 Design of experiment

Case	No. of input variable	No. of hidden layer	No. of neuron in hidden layer	
			1st hidden layer	2nd hidden layer
1	121	1	50	•
	36	1	50	•
2	36	1	72	•
	36	1	50	•
3	36	2	50	20
	36	1	50	•

Table 5 The training result of neural network

Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 31,312				Input variable : 121 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 18,228			
1st surface	2nd surface	3rd surface	Correct answer	1st surface	2nd surface	3rd surface	Correct answer
11	9	11	93.9%	10	11	11	97.0%

Table 6 Training result of neural network

Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 72 Cycle : 26,595				Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 31,312			
1st surface	2nd surface	3rd surface	Correct answer	1st surface	2nd surface	3rd surface	Correct answer
11	9	11	93.9%	11	9	11	93.9%

of neurons in hidden layer, such as 26,595 cycles.

(C) Case 3

In this case, different numbers of hidden layer are considered. Namely, the numbers of hidden layer are divided into two kinds of hidden layers such as 1 and 2. One hidden layer has 50 neurons and the other hidden layer has 20 neurons in first, 50 neurons in second. The training results of neural networks are described in Table 7. As can be observed from the table, when hidden layer is single, neural networks show the correct prediction rate more efficiently such as 93.9%. However, single-layer nets takes more cycles than two hidden layers from the standpoint of the training cycle. The correct prediction rate in two hidden layers shows lower than single-layer nets. Nevertheless, it can be said that if hidden layer is increased, then the neural network can classify more complicated patterns of ship hull surface quickly with the almost same level of correct answer rate than single layer net.

3.2 Test result of non-trained hull surfaces

Using the neural networks learned above, non-trained hull surface is tried to be classified and the prediction rate is compared. At this time for the prediction, ten test input data are prepared for three kinds of ship hull. The test results of neural network are described in Tables 8 and 9. As can be observed from the tables, the test results stated in Table 8 show similar trend with the training results. The case of two hidden layers with many input variables (121) shows more efficient neural networks in surface classification. The correct answer rate is 96.6%. As a result, it can be concluded that the ship hull is possible to be classified effectively by applying the neural network

Table 7 Training result of neural network

Input variable : 36 Hidden layer : 2 No. of neuron in hidden layer : 20, 50 Cycle : 10,445				Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 31,312			
1st surface	2nd surface	3rd surface	Correct answer	1st surface	2nd surface	3rd surface	Correct answer
11	9	10	92.9%	11	9	11	93.9%

Table 8 Test result of neural network

Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 31,312				Input variable : 121 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 18,228			
1st surface	2nd surface	3rd surface	Correct answer	1st surface	2nd surface	3rd surface	Correct answer
9	9	10	93.3%	9	10	10	96.6%

Table 9 Test result of neural network

Input variable : 36 Hidden layer : 1 No. of neuron in hidden layer : 50 Cycle : 26,595				Input variable : 36 Hidden layer : 2 No. of neuron in hidden layer : 20, 50 Cycle : 10,445			
1st surface	2nd surface	3rd surface	Correct answer	1st surface	2nd surface	3rd surface	Correct answer
9	9	10	93.9%	10	8	9	92%

pattern classification. Accordingly, the necessary manufacturing processing cost can be calculated more efficiently. And it can be said that there is a possibility of an economic hull development.

By the way, the error is included in the results of all cases, which can be explained from the stand point of used input and output information. In addition to the net architecture, the reason why there is still error exist is the selection of input patterns and the accuracy of the shell expansion.

4. Conclusion

In this study, the problem of improving the efficiency of the design at the initial stage has been dealt with from the need of supporting the preliminary ship design using artificial intelligence. The neural network as one of artificial intelligence technique is applied to design technique. In order to apply artificial intelligence to the preliminary ship design, several cases belonging to the typical ship design activities are chosen. In experiment, this study investigated that the ship hull can be classified effectively by applying the neural network to the pattern classification in ship design. Several cases of training are carried out and the pattern recognition by neural networks is proved very helpful in pattern classification of hull plate problems in ship design.

As a result, it can be concluded that the proposed method can classif effectively and efficiently the various shape of ship hull. Accordingly, it can calculatey the necessary manufacturing processing cost more efficiently. And it can be said that there is a possibility of an economic hull development. The results reported herein will provide a better understanding in classifying a ship hull by using the pattern classification of the neural network. Moreover, it is believed that this study can be utilized to provide the methodology of intellectual ship design.

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References

Choi, B. K., 1991, "Surface Modeling for CAD/CAM," ELSEVIER, Amsterdam-Oxford-New York-Tokyo.

Freeman, A. and Skapura, M., 1991, "Neural Networks (Algorithms, Applications, and Programming Techniques)," *Addison-Wesley Publishing Company*, Califonia.

Hwangbo, S. M. and Shin, H. J., 2000, "Statistical Prediction of Wake Fields on Propeller Plane by Neural Network using Back-Propagation," *Journal of Ship and Ocean Technology*, Vol. 4, No. 3, pp. 1~12.

Kim, W. D., 1991, "Direct Fairing for Geometric Modeling of Hull Surface," *Journal of Ship and Ocean Technology*, Vol. 28, No. 1, pp. 1~11.

Laurene Fausett, 1994, "Fundamentals of Neural Networks : Architectures, Algorithms, and Applications," *Prentice-Hall*, Inc..

Mamdani, E. H. and Assilian, S., 1975, "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller," *International Journal of Man-Machine Studies*, Vol. 7, No. 1, pp. 1~13.

Marenn, A. J. Jones, D. and Franklin, S., 1990, "Configuring and Optimizing the Back-Propagation Network : Handbook of Neural Computing Applications," Academic Press.

Rogers, D. F. and Adams, J. A., 1990, "Mathematical Elements for Computer Graphics," *McGraw-Hill Publishing Company*, International Edition.

Rosenblatt, F., 1958, "The Perceptron : A Probabilistic Model for Information Storage and Organization in the Brain," *Psychological Review*, Vol. 65, pp. 386~408.

Shar, S. and Palmieri, F., 1990, "MEKA-a Fast, Local Algorithm for Training Feed Forward Neural Networks," In Proc. of International Joint Conference on Neural Networks, pages III 41~46.

Stuart Russell, Peter Norvig, 1995, "Artificial Intelligence — A Modern Approach," Prentice Hall, Inc..

Valluru, B. Rao and Hayagriva, V. Rao, 1993, "C++ Neural Networks and Fuzzy Logic," *Management Information Source*, Inc., pp. 103~147.

Ye, X., 1994, "Construction and Verification of Smooth Free-Form Surfaces Generated by Compatible Interpolation of Arbitrary Meshes," The Technical University of Berlin.