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Neurofuzzy System for an Initial Ship Design

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ABSTRACT

The purpose of this paper is to develop a neurofuzzy modeling & inference system which can determine principal dimensions and hull factors in an initial ship design. Neurofuzzy modeling & inference for a hull form design (NeFHull) applies the given input-output data to the fuzzy theory. NeFHull also deals the fuzzificated values with neural networks. NeFHull redefines normalized input-output data as membership functions and executes the fuzzficated information with backporpagation-neural-networks. A hybrid learning algorithm is utilized in the training of neural networks and examining the usefulness of suggested method through mathematical and mechanical examples.

1. Introduction

In an initial hull design, available information is generally limited, and design factors include many nonlinear properties. We must consider each information to express as practical knowledge or numerical values at the same time. Therefore design works in a shipyard had executed practically with parent ships and accumulated experiences of designers. An intelligent system could help designer's decision so that these design works could be carried out rapidly and precisely.

An intelligent system should be utilized using either (a) an expert knowledge system as expert system, knowledge based system or (b) a system composing internal knowledge from experienced data as a fuzzy system, neural networks.

It is difficult to secure and express the design expert's knowledge in a special field with (a). While (b) requires a precise and reliable data to express the internal knowledge obtained from the experience. Knowledge can be obtained through a learning process in a neural network. But learning process is slow and it is difficult to interpret learned neural network. A fuzzy system is based on fuzzy rule and inference, so it is possible to improve its performance by controlling rules. But it takes too much time to code by using a rule of natural language level directly from the expert's knowledge.

Thus, we realize a knowledge system with interactive characters by combining a fuzzy system and a neural network. Then we can apply them in a hull design.

Neurofuzzy system is explained below.

- **Modular Network [1][2]**

The purpose of Takagi & Hayashi's modular network development is that it modularizes weight of premise and output of conclusion in fuzzy if-then rule using a neural network. It provides the control power to the system. Then it systemizes internal ouput, the weight and the output of each rule, using modular network and improves adaptive power for an environment of fuzzy inference system.

- **ANFIS [3]**

The purpose of ANFIS development is that it improves the learning speed and the adaptive power of membership function using a learning process. Then, it composes fuzzy inference system's structure to the neural network. Then the learning process controls the parameters using a steepest descent method. These parameters define membership function of premise in fuzzy if-then rule. It determines parameters of conclusion by using Kalman filter algorithm[4]. It makes an optimum fuzzy inference system within the given condition.

- **ASMOD [5][6]**

The purpose of ASMOD development is that it makes an optimum system that decreases dimension of input variable increasement and creates reasonable ouput. Then each membership function is defined by a B-spline basis function, and the complicacy of system was minimized as expressing the total system model by summing the submodels.

We consider the neurofuzzy system and its property in this paper. When we design a ship, we have to understand the geometrical and physical correlation for the design condition, the principle dimension, the performance coefficient, the geometrical characters of a hull form and so on. A neurofuzzy system for a hull design was developed for that purpose.

2. Neurofuzzy Modeling & Inference System for a Hull Form Design

2.1 Structure of a NeFHull

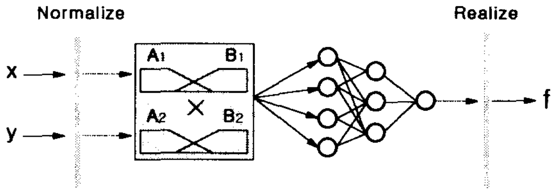
NeFHull(Neurofuzzy modeling & inference system for a hull form design) can be systematized after we disperse and arrange information to given input-output data in order to design a hull form with a fuzzy rule[7]. We apply to neural network[8].

NeFHull can be explained with equation (1).

$$\textit{Premise}\begin{cases} p^1 : \textit{If } x_1 \textit{ is } A_1^1 \text{ and } x_2 \textit{ is } A_2^1 \text{ and } \cdots, x_m \textit{ is } A_m^1 \\ p^2 : \textit{If } x_1 \textit{ is } A_1^2 \text{ and } x_2 \textit{ is } A_2^2 \text{ and } \cdots, x_m \textit{ is } A_m^2 \\ \vdots \\ p^n : \textit{If } x_1 \textit{ is } A_1^n \text{ and } x_2 \textit{ is } A_2^n \text{ and } \cdots, x_m \textit{ is } A_m^n \end{cases}$$

$$\oplus$$

$$\textit{Conclusion} : \quad \textbf{[}\textit{Neural network}\textbf{]} \qquad (1)$$



Where, x_i is a design parameter.

A_j^i is a fuzzy membership function with a trapzoidal type.

p^i is i'th fuzzy rule, but it's i'th pattern information rule in a sence of composing input pattern of neural network. Its collection is a premise, and neural networks structure is a conclusion. "$\oplus$" presents that output in previous step connects input pattern to the next step. Fig. 1 presents a NeFHull structure, 2-inputs & 1-output.

Fig. 1 The structure of a NeFHull with 2-inputs & 1-output

2.2 Partitions of Fuzzy Space

When design factors are added, a NeFHull is mapping their information to fuzzy space and disperse input information. If the number of input variable increases, fuzzy rules increase according to the dimensions of design space. In this paper, we try to overcome above problem as representing a total NeFHull model with the summation of submodels. That is, it makes submodels with correlated input variables, and each of submodel is executed with fuzzy partitions. Finally, the total model is summed each of submodel and desired outputs. The composing formula has a total pattern information and is expressed in equation (2).

$$p^i(\boldsymbol{x}) = s_1(\boldsymbol{x}_1^*) + \cdots + s_n(\boldsymbol{x}_n^*) \quad (2)$$

where, $\boldsymbol{x}$ is a total input variable vector, $\boldsymbol{x}_j^*$ is a part of input variable vector satisfied in $\boldsymbol{x}_j^* \subseteq \boldsymbol{x}$, p^i is a i'th pattern information rule and s_j is a submodel composing j'th pattern information rule. Fig. 2 represents information disperse process as the concept of submodel.

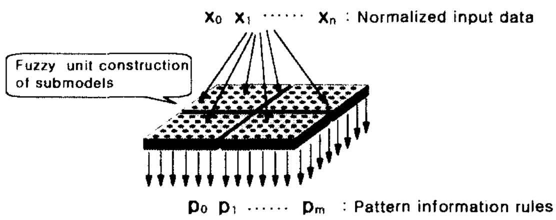


Fig. 2 The process of information distribution splittering in a NeFHull

For example, let the number of input variable(x_i) be six. If each variable has natural language variable of three kind 'big', 'medium', and 'small', then the total fuzzy space partition is $3^6 = 729$. If a total model is taken apart submodels like equation (3) considering correlation of input variables.

$$p^i(a_1, \cdots, a_6) = s_1(a_1,\ a_3,\ a_4) + s_2(a_2,\ a_5) + s_3(a_1,\ a_2,\ a_6) \quad (3)$$

In this case, the total fuzzy space partition is $3^3 + 3^2 + 3^3 = 63$, and represents a reduced dimension of design space.

2.3 Learning Algorithm of a NeFHull

A NeFHull learning process is made up of two steps.

Step 1, structure recognition of premise pattern information rule.

Step 2, structure recognition of conclusion pattern information rule and is carried out.

Before training, it has to be defined the following conditions.

① Input variables and fuzzy membership functions for each variables are established.

② Submodels are composed from physical and geometrical relationship of input variables.

③ Each number of the input-output variables of neural networks is determined.

④ Each number of the hidden layers and neurons is determined.

⑤ Establishment method for initial connect weight, learning rate, momentum, bias, etc. is determined.

Once the above conditions are determined, a NeFHull is able to carry out the training process using the three type learning methods.

(1) Type 1

Type 1 determines the premise and the conclusion from experiences. This is a learning process to give the enough learning number for minimizing the performance standard. This method helps reaching to the allowable range. This type has risks to be a predominamt convergence or to fall into a local minimum solution. Output is affected to initial conditions that are selected by the designer.

(2) Type 2

In this case, the learning number is fixed. The parameters is determined without a rule. The parameters composes the fuzzy membership function. In Type 2, a repeated learning process will be carried out as indicated below.

[step 1] Once the structures of premise and conclusions are decided. The learning number is fixed accordingly.

[step 2] Fuzzy membership functions compose the premise. The parameters compose the fuzzy membership functions. Then the parameters are established without a rule.

[step 3] A learning process will be carried out according to the given premise's structure and the learning number. Whenever the learning process is over, it saves information to connect the weight. When new learning starts, it refers to above information.

[step 4] It will be repeated with [step 2] and [step 3] until it satisfies the final condition (allowance error range).

This type has no risks to fall into the local minimum solution. Because it is recognized the structure of neural networks in the past, changing parameters without a rule. Fuzzy membership functions consist of parameters. It has difficulty to recognize the neural networks's exact structure for a given problem.

(3) Type 3

Type 3 is a combination of Type 1 and Type 2. After carrying out a global searching using Type 2, it determines an optimum NeFHull's structure using Type 1. Type 3 is used as a learning method in this paper.

3. Application of NeFHull

To be convinced of the numerical inference process's effectiveness and usefulness in an initial ship design, we can apply a NeFHull for ship dimension estimation.

3.1 Application to Ship Dimension

A NeFHull is applied to estimate principle dimensions according to the ship initial design condition. Table 1 presents design conditions and design factors. Type of ships are bulkers and tankers.

Table 1 Design conditions and variables

45×10^3	$\leq$	Deadweight(Ton)	$\leq$	310×10^3
11.0	$\leq$	Ship velocity(Knot)	$\leq$	16.0
9.5	$\leq$	Draft(m)	$\leq$	21.4

Total 20 real ships are used. 18 shipsl (bulker: 6 , tanker: 12) are used for modeling and 2 ships (bulker: 1 , tanker: 1) are used for a model testing. We carried out a NeFHull modeling for the principal dimensions (length between perpendiculars: Lbp, breadth: B) and examined the results.

NeFHull learning method : Type 3.

Learning period : 200

Total learning number : 102,000

In the first stage, learning number of Type 2 : 200

In the second stage, learning number of Type 1 : 101,800

Learning rate : 0.8

Momentum : 0.3

Output layer's neuron is Lbp and B.

Fig. 3 represents NeFHull fuzzy membership functions of each input variable after modeling a NeFHull.

Fig. 3 Premise fuzzy units resulted by NeFHull modeling for Lbp & B

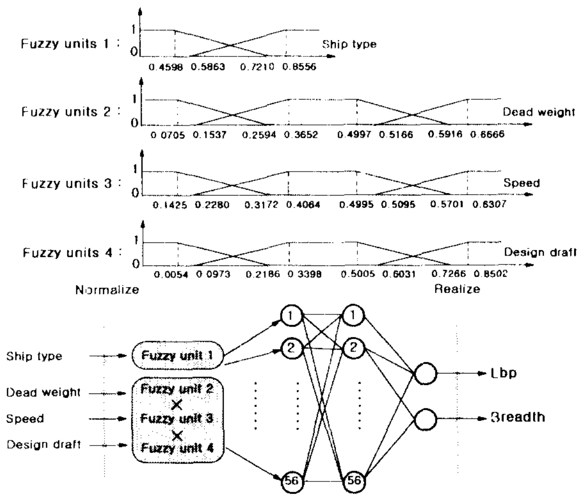


Fig. 4 The structure of a NeFHull for Lbp & B

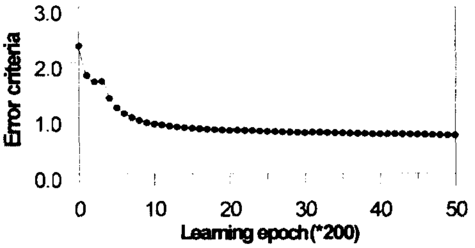
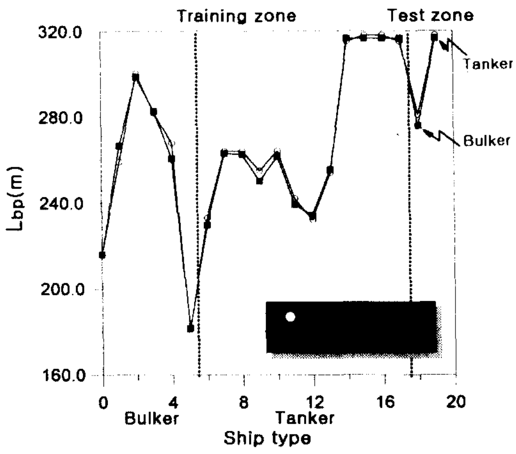
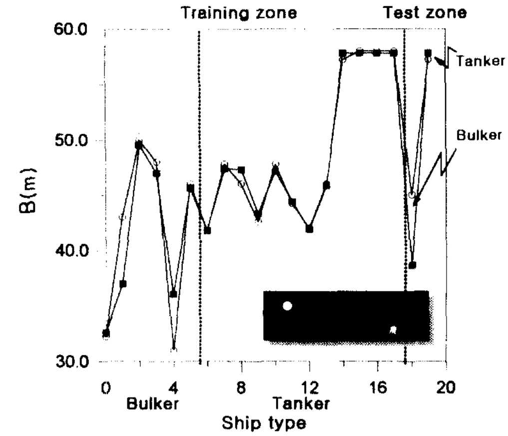


Fig. 5 The progress of error criteria during the learning of a NeFHull for Lbp & B



(a)



(b)

Fig. 6 Comparision real values and values inferred by fuzzy neural networks modeling for Lbp & B

Fig. 4 represents a NeFHull fuzzy membership connection method and neural networks' structure.

Fig. 5 represents the progress condition of an error while learning process is carryied out.

Fig. 6 is a comparison of a real value and an inference value for the learning data using modeling and test data without using modeling. In case of Lbp, the error for learning data is 1.4%, and in case of B, the error for learning data is 3.4%. Total average error is 2.4%.

The results of the NeFHull modeling represent real values very well, and are able to consist the interactive connected system as considering 2-ouput at the same time through neural networks. When we estimate Lbp by a NeFHull, tanker's estimated value is more accurate than bulker's estimated value. The reason is that the number of input-output variable for tanker is two times the bulker's variable, so inner knowledges of a NeFHull has established with the center of tanker's database.

If input-output data were given abundantly, a NeFHull can infer more available values. This means making a neurofuzzy system accumulate real ship data safer and safer as real ship data are accumulated by neural networks's characters.

4. Conclusions

① A NeFHull is utilized to realize parsimonious neurofuzzy system for a hull design through the submodel concept.

② A NeFHull uses a hybrid learning algorithm and decreases risk to fall into the local optimum solutions in the structure recognition of system. That is, first it selectes parameters of premises randomly and trains neural networks in conclusions. Then it searchs global optimum solutions.

③ A NeFHull has multi-inputs and multi-outputs. Therefore it can be used efficiently in a ship design which should determine design variables with the correlated design conditions.

5. References

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