LVQ Neural Network Based Classification Decision Approach to Mechanism Type in Conceptual Design

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Abstract. A decision approach to mechanism type selection is presented, which employs LVQ neural network as classifier and decision-maker to recognize a satisfactory mechanism from a range of mechanisms achieving a required kinematic function. Through learning from correct samples extracted from different mechanisms, expert knowledge is acquired and expressed in the form of weight matrix by LVQ network. When selecting mechanism type, through digitizing the design requirements, converting into a characteristic factor set, and fed into the trained LVQ network, a satisfactory mechanism can be automatically recognized from a range of mechanisms with the same kinematic function. Under this approach, the problem of knowledge acquisition and expression can be effectively solved, and the rationality of the decision can be improved at some extent. It is verified this approach is feasible to perform mechanism type selection and possesses a better characteristic of pattern classification compared with BP neural network.

Keywords: Mechanism type selection, LVQ neural network, Knowledge acquisition, Mechanical design.

1 Introduction

An approach of function decomposition is generally adopted in conceptual design of mechanical system [1]. The first step is to acquire the general-function of mechanical product. Then using function decomposition, a complicated design problem regarding general-function can be divided into many simple design problems regarding function units. For each function unit, a sequence of function carriers are searched using design catalogue [2]. The following step is to select one satisfactory mechanism in above function carriers, which is called a problem of mechanism type selection. Commonly used approach to this problem is implemented by designers according to their domain experience, which will undoubtedly result in the limitations and blindness of the decision result if domain experience is poor.

Neural network has proven to be an effective and powerful tool to implement mechanism type selection in conceptual design since it possesses the features of non-linearity, self-organization, and fault-tolerance. BP and ART neural network are two popular networks for this purpose [3]. However, the decision performance of BP is affected by its network structure (e.g., the number of layer and node of hidden layer)

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at a large extent, and its node function has a heavy impact on its learning rate and quality. ART network is also affected by its network structure, moreover, similarity discriminant function, standardization and denoising preprocessing function of F1 layer needs to be constructed, which also affects the performance of this network.

Compared with these two networks, LVQ network possesses simpler network structure, faster learning rate, more reliable classification, and better fault tolerance. Thus LVQ neural network is employed as classifier to recognize a satisfactory mechanism from a range of mechanisms through learning and accumulating the domain expertise. The reasoning process of evaluation and decision can be automaticlly implemented and the process of conceptual design can be simplified at some extent.

The remainder of this paper is presented as follows. First, we present the basic process and principle of mechanism type selection based on ANN. Then we propose fuzzy quantization method of the characteristic factor value. Next this LVQ neural network based decision model is illustrated in detail, including the structure of neural network, training and testing, etc. Finally concluding remarks are given.

2 Technical Preliminaries

2.1 Problem Statement

Mechanism type selection can be viewed as a decision problem regarding satisfactory mechanism type on the basis of considering multi-factors synthetically. That means, a decision problem involves six elements, viz. [V, U, W, P, D, R]. V represents the decision set, viz. $V = \{V_1, V_2, \ldots, V_m\}$, which is a set of m types of mechanisms for decision. U represents a characteristic factor set, viz. $U = \{U_1, U_2, \ldots, U_n\}$, which is a set of n types of characteristic factors to be considered, where n equals 5 and U_1, U_2, U_3, U_4, and U_5 respectively stand for Working performance, Kinetic performance, Economy, Maneuverability, and Structural compactness. W represents the weight set, viz. $W = \{W_1, W_2, \ldots, W_n\}$, which shows the importance of each characteristic factor. U and W constitute an evaluation index system. P is called a pre-processor used to transform each evaluation index into the allowable input value for the decision model. D represents the decision model for mechanism type selection, and R represents the decision result [4].

2.2 Decision Principle

The problem of mechanism type selection can be regarded as a pattern classification and recognition problem, viz. classifying different patterns by extracting their typical features and recognizing the result pattern through matching the known design conditions [5]. Here, the characteristic factor set in Table 1 actually represents the optimum application conditions for each mechanism, called the typical characteristic factor set U*. When selecting mechanism type, each performance index determined by design requirements can be fuzzily quantified and constitute a characteristic factor set U, then a type of mechanism is selected according to the above typical characteristic factor set U*, which is the fittest mechanism for characteristic factor set U. The decision can be implemented based on the closeness degree between U* and U by valuators, which is an experiential selection mode in nature. Whereas LVQ neural network has the advantages in classification and decision over BP or ART, it acts as a Classifier and decision-maker for selecting mechanism type through modeling the nonlinear relations between input and output data. When an optimum mechanism is required to be selected from a series of mechanisms achieving a certain function, the typical characteristic factor set U* for each mechanism is regarded as the training sample to train the neural network first, then the required factor set U derived from design requirements is fed into the trained network, finally through the decision a suited mechanism type is exported. This process is facilitated by the way in which the model acts as a knowledge base and reasoning engine for decision. The decision process incorporates the evaluation and ranking process and to some extent it simplifies the process of conceptual design.

2.3 Decision Process

A neural network based decision model is applied to implement mechanism type selection. The decision process is shown in Fig. 1.

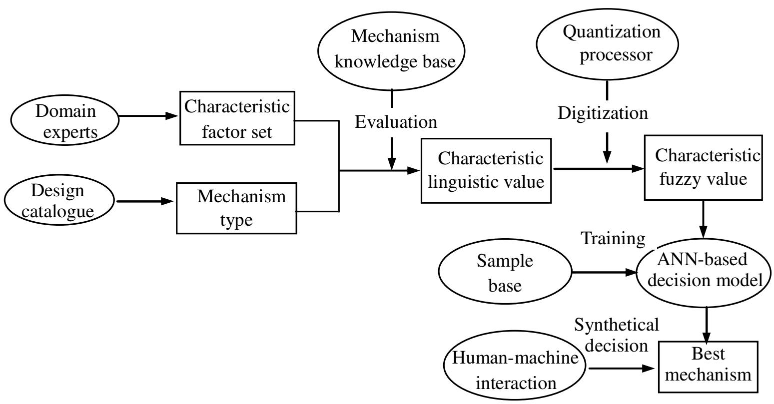

Fig. 1. Process of mechanism type selection

3 Feature Digitization and Extraction for Typical Mechanism

It is obvious that the input values of neural network are numerical data. However, the expressive meanings of above–mentioned characteristic factors of mechanisms are fuzzy in nature, which are usually expressed in a linguistic mode according to the valuator's experience. As a result, it is required to convert this linguistic expression into numerical data. Fuzzy set theory is proved to be an effective tool in implementing a comparative precise quantization for characteristic factor [6]. Through building the membership function for each factor and calculating the corresponding membership degree, a quantitative measurement can be obtained. For example, for the characteristic factor of structural compactness, the number of kinematic pairs, can be used as an independent variable of the membership function, viz. x, the maximum and the minimum membership degrees for the mechanism are respectively 1 and 0, and a membership function in the form of a descending half-trapezoid is obtained.

Using this membership function, the membership degree for the mechanisms with different numbers of kinematic pairs can be calculated. For those characteristic factors, which cannot be easily measured by constructing linear membership function, a fuzzy statistical method or duality contrast ranking method can be used to implement the quantization process. Under this disposal, semantic expression values of characteristic factors are digitized and features of different mechanisms are extracted. Table 1 gives the characteristic factor values of four types of typical mechanisms used to convert continuous rotation into intermittent rotation in a kinematic scheme design of a certain machine tool, viz.Geneva mechanism(V_1),Imperfect gear device(V_2), Cam intermittent mechanism(V_3), and Internal epicycle intermittent mechanism(V_4) [7].

Table 1. Characteristic values and classification values of typical mechanisms

Drive type	Characteristic value					Classification value			
	U_1	U_2	U_3	U_4	U_5	1	2	3	4
V_1	0.95	0.25	0.95	0.65	0.65	1	0	0	0
V_2	0.90	0.20	0.15	0.72	0.60	0	1	0	0
V_3	0.85	0.95	0.15	0.70	0.65	0	0	1	0
V_4	1.00	0.70	0.10	0.68	0.80	0	0	0	1

4 LVQ Neural Network Based Decision Model

4.1 The Structure of Network Model

Learning Vector Quantization (LVQ) is a learning algorithm that combines competitive learning with supervision [8]. It was originally suggested by Kohonen. A LVQ network is a two-layer neural network, including a competitive layer and a linear layer. The competitive layer is the core layer that performs classification through learning. Each neuron in the competitive layer of the LVQ network learns to recognize a prototype vector, which allows it to classify a region of the input space. In using LVQ networks, we directly calculate the distances between the input vectors and the prototype vectors to achieve classification. If two input vectors are close to each other, they belong to a same class. A basic LVQ network is shown in Fig.2. In this figure, R is the number of element of input vector, S is the number of neuron, P is the input vector, W is the weight matrix, and A is the output vector. The competitive layer performs classification of input vectors, and the linear layer converts the classification information into the desired class defined by user and output them automatically. Therefore, the neuron whose weight vector is closest to the input vector will output 1, and the other neurons will output 0.The input vector contains R nodes for R input features, the competitive layer contains equal numbers of nodes for each class, and in the output layer, each output node represents a particular class. It is obvious that the input vectors can be classified into N classes if the LVQ network possesses N neurons. In the decision model, for the reason that there are 5 characteristic factors serving as input values, the number of nodes for the competitive layer is 5 and the number of nodes for the linear layer equals the number of mechanisms in the decision set, in which each mechanism corresponds to an output node and different nodes represent different mechanism types. For the decision model constructed by the data of Table 1, it is obvious that the number of nodes for the linear layer is 4 and its output classification is also given in Table 1.

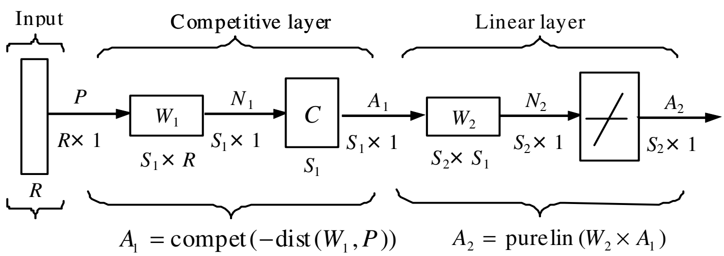

Fig. 2. Structure of LVQ neural network

4.2 Learning and Simulation

Since LVQ performs learning with supervision, correct training samples are required to be provided for neural network's training. The quality of samples has a critical influence on the performance of network. Once the training process terminates, the classification surface is fixed and the corresponding decision system is formed. In this decision model, training samples are typical characteristic factor sets of various mechanisms in decision set. Here, characteristic factor values of 4 types of mechanisms in Table 1 employed as input data, and the corresponding classification results in Table 1 employed as output data, constitute four pairs of training samples from 1 to 4, as shown in Table 2, which can be fed into the network to train it. Neural network toolbox of Matlab 6.5 affords facilities for this learning and training process. First, the LVQ network is constructed by a "newlvq" function provided by neural network toolbox of Matlab 6.5. Then a training function called "train" is applied to implement the training to get the weight matrix. The network is convergent at last after 150 epochs of iteration. Thus it can be employed a decisionmaker to select an appropriate mechanism from a group of mechanisms.

In order to know the performance of this network, a testing process is required to implement after the LVQ have been trained. Here, a "sim" function is used to implement simulation. The character factor values for mechanism can be obtained first according to the concrete design requirements, which is expressed with linguistic mode. Then through fuzzy quantization, the corresponding characteristic factor values are obtained, which can be used as input vectors of this trained network. In Table 2, the vectors from 1 to 4 are fed into the network to implement simulation, and correct decision results are given. The rest of the samples are testing samples derived from other design problems, in which the input values of the 5th and 6th samples are close to the values of a certain mechanism respectively and the correct decision result is given, moreover, the values of the 7th and 8th samples are between the values of two types of mechanisms, which is a difficult decision problem, and where a certain mechanism is selected using this model. The above simulation result shows LVQ classifier has the advantage of better fault torlance and stability over other neural networks.

Table 2. Recognition results of the LVQ network

Sample	Input					Output				Expected result	Decision result
	U_1	U_2	U_3	U_4	U_5	V_1	V_2	V_3	V_4		
1	0.95	0.25	0.95	0.65	0.65	1	0	0	0	V_1	V_1
2	0.90	0.20	0.15	0.72	0.60	0	1	0	0	V_2	V_2
3	0.85	0.95	0.15	0.70	0.65	0	0	1	0	V_3	V_3
4	1.00	0.70	0.10	0.68	0.80	0	0	0	1	V_4	V_4
5	1.00	0.30	0.95	0.50	0.50	1	0	0	0	V_1	V_1
6	0.90	0.35	0.25	0.70	0.50	0	1	0	0	V_2	V_2
7	0.85	0.60	0.65	0.60	0.60	1	0	0	0	V_1 or V_3	V_1
8	0.85	0.20	0.95	0.80	0.50	0	1	0	0	V_1 or V_2	V_2

5 Conclusion

In this paper, an approach to mechanism type selection is proposed according to the nonlinear mapping and clustering characteristic of LVQ neural network. This approach employs neural network as a tool to implement the reasoning process of evaluation and decision-making, in which the process of conceptual design can be simplified at some extent, the problem of the expression and accumulation for expert knowledge can be effectively solved, and the rationality of the decision can be improved. It is concluded that the LVQ network based decision model developed is appropriate to be used for selecting mechanism type at the early design stage.

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