Research Article
A Conflict Detection Model Based on Constraint Satisfaction in Food Product Collaborative Design

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Abstract: With the market competition increasing, in order to shorten product development cycle and reduce the development costs, product design is changed from the traditional serial-type process to the parallel, collaborative development process. Food product collaborative design of Feature modeling refers to the number of the design team through the division of labor and cooperation has completed a product development project process. The set with known constraints was detected by interval propagation algorithm. Meanwhile, BP neural network was proposed in this study to detect the set with unknown constraints. Simulated results indicated that BP neural network optimized by IA has better performance in convergent speed and global searching ability compared with Genetic Algorithm (GA).The constraints of two sets were detected respectively.

Keywords: BP neural network, conflict detection, food product collaborative design

INTRODUCTION

As an important branch of CSCW, food product collaborative design is considered as a group-working style based on effective communication and cooperation for complex product. Designers form different disciplines participate in the food product collaborative design process. The variables of designers are interrelated, interdependent and mutual restraint. Conflicts inevitably occur because of different background knowledge, different views of issue and different standards of evaluation. In consequence of reducing the efficiency of design, conflict detection is regarded as one of the important functions in food product collaborative design. So far, no effective way is proposed to detect conflicts in food product collaborative design.

To detect conflicts effectively in food product collaborative design, extensive research has been conducted. Pierre (2009) considered that the design process can be modeled in the form of a Constraint Satisfaction Problem (CSP). Meng *et al*. (2004) described the CSP in a formal expression and explored the problem of conflict detection. Hu *et al*. (2009) investigated a method of conflict detection based on vertical constraint network model. Slimani *et al*. (2006) proposed to eliminate conflicts by sharing and exchange knowledge in food product collaborative design process. Zhu and Song (2012) put forward a conflict detection algorithm based on the design history in collaborative CAD design. Zhao *et al*. (2002) and Xie *et al*. (2002) used constraint verification and interval propagation algorithms to detect the conflicts. Wang and Jin (2007) proposed a consistency model of operation sequence and conflict detection algorithm based on geometry level. Xiong *et al*. (2009) raised an approach of distributed conflict detection for supporting concurrent design.

However, the existence of massive implicit conflicts causes that the exact ranges of some constraints are difficult to be determined. Conflicts can't be detected comprehensively and accurately. Based on the hierarchical constraints and constraint satisfaction, this study raises a detection method of conflict, which provides a theoretical basis for the conflict digestion (Jaulin, 2000).

MATERIALS AND METHODS

There are many types of constraints in food product collaborative design, such as design constraints, process constraints, manufacturing constraints, etc. They are associated with the product attributes, formed as a network and constituted the boundary of the possible design solutions. Each design problem can be converted to a solution process based on the constraints network. Conflicts will occur when the constraints cannot be satisfied.

Analysis of hierarchical constraints: During the food product collaborative design process, design goals are mapped onto the product object tree with hierarchical structure. From the top to bottom of the tree, there are product, component, part and feature. Figure 1 shows
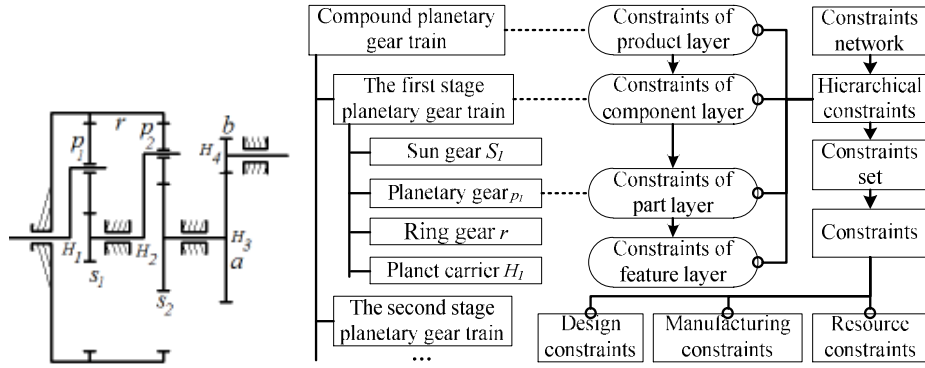
Fig. 1: Transmission diagram of compound planetary gear train and its constraints

the transmission diagram of a compound planetary gear train and the relationships between the object tree and hierarchical constraints.

Constraints reflect the restrictive relationships between the product and design purposes. Taking food product collaborative design of wind planetary gear train for example, the constraint network can be divided into layers of product, component, part and feature. The layer of product describes the product performance, weight and structures, such as train power and transmission ratio, etc. The layer of component describes the design requirements of component and the constraints among the different parts, such as design of sub gear train and design of cabinet, etc. The layer of part describes the design requirements of the parts, such as design of gears and shafts, etc. The layer of feature describes the design parameters of the parts, such as geometry dimensions and strength requirements of the parts, etc.

The interaction between different levels of constraints can be reduced since the controllable network of hierarchical constraints has been set up. It is convenient to manage the relationships of constraints when the design attributes change. As shown in Fig. 1, if the teeth number of the sun gear changes, designers have only to modify the corresponding layer of part. The constraints of different layers are related. When conflicts of a high-level constraint have occurred, the lower levels that caused the conflict can quickly be found. Conflicts can be detected through verification of constraints form layer to layer, starting from the layer of feature.

Analysis of constraint satisfaction: The solutions of the constraint network can be expressed by CSP, according to the following equation:

$$K(X) = \left\{ (X_1 = x_1, X_2 = x_2, \cdots, X_n = x_n) \middle| \forall c_i \right. \tag{1}$$

$$\left. \prod V(c_i) R(c) \subseteq R(c_i) \right\} \tag{2}$$

where, $\prod V(c_i) R(c) \subseteq R(c_i)$ is the projection of variables set $V(c_i)$ in constraints set $R(c_i)$. If Eq. (1)

has a solution, it indicates that there is no conflict. While there is no solution, conflicts occurred.

The food product collaborative design is a continuous process of discovering and digesting conflicts. So it's impossible to confirm all the possibility constraints of design variables before the design has been completed. With the deepening of the design, identified constraints may change constantly and new constraints will appear. However, some constraints can't be expressed specifically, such as resource allocation, data sharing and data cooperating between different design departments. Therefore, the set of constraints C can be divided into one set C_1 with known constraints and another set C_2 with unknown constraints. Unknown constraints may convert into known constraints in the design process and the set of constraints can be written as:

$$\begin{cases} C = C_1 \cup C_2 \\ C_1 = f_1(X, D) \\ C_2 = f_2(X, D) \end{cases} \tag{3}$$

The solution of conflicts in food product collaborative design process can be transformed to the solution of Eq. (3), so as to make sure whether the conflicts have happened or not.

Design of conflict detection model: The set of constraints C_1 can be verified directly by the interval propagation algorithm (Klein, 1991). The implicit conflicts make it difficult to confirm some constraints of the set of C_2, which can't be solved by interval propagation algorithm. The relationship between constraints and conflicts is highly nonlinear and the influence of constraints impacting on conflict is different. BP neural network can approach the complex nonlinear system in arbitrary precision. It gets a good application in the multivariate nonlinear problems, such as fault diagnosis and life prediction (Avila *et al.*, 2008; Yuan *et al.*, 2014). But BP neural network has the disadvantages of slow convergence rate, local extreme point and weak generative ability. Based on the
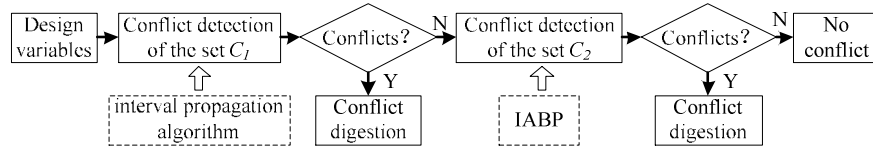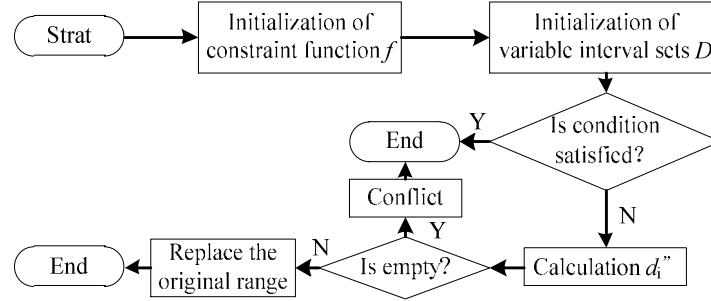
Fig. 2: Process of conflict detection

Fig. 3: Detection process based on interval propagation algorithm

biological immune mechanism, Immune Algorithm (IA) is an improved genetic algorithm, which is combined the immune theory with genetic algorithm (Zhang *et al.*, 2008). On the basis of retaining the global random searching ability, it involves the mechanisms which exist in biological immune system such as antigen recognition, antibody diversity, immune memory, antibody encouragement and restraint, antibody diversity keeping, etc. It avoids premature and guarantees that result converges to the global minimum.

This study uses interval propagation algorithm to detect the set of constraints C_1, while the set of constraints C_2 is simulated by BP neural network. IA is utilized to optimize the BP neural network's weights and thresholds (IABP). IABP not only improves the mapping ability of generalization, but also ensures algorithm convergence rapidly in globally optimal solution and strong learning ability. Finally, it can accurately detect whether there is conflict or not. Figure 2 shows the detection process of food product collaborative design.

Description of algorithm: According to the interval propagation algorithm, the answer of design variable x_i by solving the set of constraints C can be written as:

$$d_i' = f^{-1}\left[R(c_i), x_i\right] \qquad (4)$$

So the new solution interval of x_i can be written as:

$$d_i'' = d_i' \cap d_i \qquad (5)$$

If the Eq. (5) is not empty, d_i will be replaced by d_i''. The feasible solution interval of all design variable x_i can be written as:

$$D' = \left[d_1'', d_2'', \cdots, d_n''\right] \qquad (6)$$

If d_i'' is empty, the constraint network is a unsolved problem and there must be conflict in food product collaborative design process. Figure 3 shows the detection process based on interval propagation algorithm.

Validation of interval propagation algorithm: As is shown in Fig. 1, the first stage planetary gear train in wind turbines gearbox consists of one sun gear, one ring gear, one planet carrier and three planetary gears. Interval propagation algorithm will be used to detect whether conflict occurs, when the adjacent planetary gear trains are installed. Figure 4 shows the constraint network of the adjacent planetary gear trains without conflict. Z_1 is the teeth number of the sun gear, Z_2 is the teeth number of the planetary gear, Z_3 is the teeth number of the ring gear and i is transmission ratio. Detection process is given by:

- Initialization of constraint function:

$$f = \left\{Z_1 \geqslant \frac{2\sqrt{3}-3}{3}Z_2 + \frac{4\sqrt{3}}{3}, Z_2 \leqslant \frac{\sqrt{3}Z_1 - 4}{2-\sqrt{3}}, Z_3 = Z_1 + 2 \cdot Z_2, \cdots\right\}$$

- Initialization of variable interval sets:

$$D = \left\{d_{Z_1}, d_{Z_2}, d_{Z_3}, d_i\right\}$$
$$= \left\{d_{Z_1} = [17, 25], d_{Z_2} = [20, 40], \cdots, d_i = [6, 8]\right\}$$

- Calculation process:

$$Z_1 \geqslant \frac{2\sqrt{3}-3}{3}Z_2 + \frac{4\sqrt{3}}{3} \Rightarrow d_{Z_1}' = [8.5, +\infty] \Rightarrow d_{Z_1}^* = [17, 25]$$

$$Z_2 \leqslant \frac{\sqrt{3}Z_1 - 4}{2-\sqrt{3}} \Rightarrow d_{Z_2}' = [0, 94.96] \Rightarrow d_{Z_2}^* = [20, 40]$$
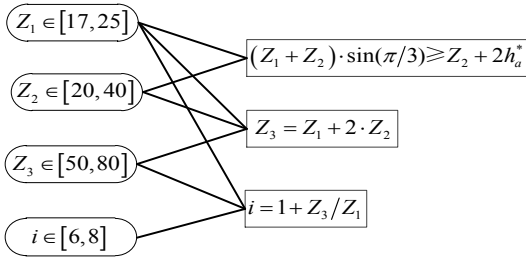$$\cdots$$

Fig. 4: Constraint network of adjacent planetary gear trains without conflict
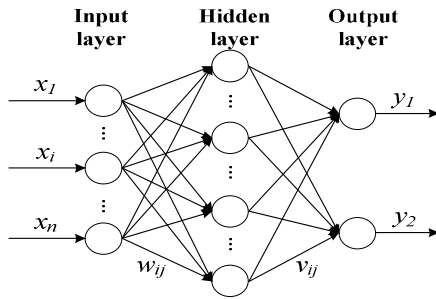

Fig. 5: BP neural network structure

$$i = 1 + \frac{Z_3}{Z_1} \Rightarrow d'_i = [3, 5.7] \Rightarrow d''_i = \varnothing$$

The results indicate that the transmission ratio is unable to meet the constraint requirements. By analyzing the reasons of the conflicts in design process, it reveals that the teeth number of ring gear can't match the transmission ratio. To eliminate conflicts, the designers should change the relationship between the teeth number of ring gear and the transmission ratio.

Model of BP neural network: Hsu *et al.* (1995) found that a three-layer BP neural network can solve random function's fitting and approximation problem. As a result, a three-layer BP neural network is adopted in this study. As shown in Fig. 5, BP neural network has three layers: input layer, hidden layer and output layer.

Input variables are composed by the design variables X ($X = \{x_1, x_2, \cdots, x_n\}$). The results of conflict detection can be divided into two kinds: one with conflicts and another without conflicts. The expression of (0, 1) represents the result without conflicts, while (1, 0) means conflicts occurred. So the number of hidden layer neurons nodes can be given by (FTRD, 2005):

$$n_2 = \sqrt{n_1 + n_3} + \alpha \tag{7}$$

where,
n_1 = The number of input layer neurons nodes
n_3 = The number of output layer neurons nodes
α = A constant, produced random among (0, 1)

The dimensions of variables and goals are different in the design process. If parameters are used to detect conflict directly, the error precision of BP neural network will reduce. Before feeding the data into BP neural network, the data must be normalized in (0.1, 0.9), according to the following equation:

$$x'_i = 0.1 + \frac{x_i - x_{min}}{x_{max} - x_{min}} * (0.9 - 0.1) \tag{8}$$

where,
x_i = The input variables for all i
x_{min} = The minimum of the data
x_{max} = The maximum
x'_i = The input variables after normalization

Learning algorithm of BP neural network: The mean square error of the actual and the target output is taken as the training error function of the BP neural network, defined as:

$$E = \frac{1}{2mq} \sum_{j=1}^{q} \sum_{i=1}^{m} \left(y_{ij} - z_{ij} \right)^2 \tag{9}$$

where,
m = The total number of samples
q = The number of output layer neurons nodes
y_{ij} = The actual output
z_{ij} = The target output

To improve the convergence speed and generalization, additional momentum method and adaptive training algorithm are used to train the BP neural network (Xu *et al.*, 2003). Weight matrix can be amended as follows:

$$w^{t+1} = w^t - \eta \left. \frac{\partial E}{\partial w} \right|_{w=w^t} + a\eta \left. \frac{\partial E}{\partial w} \right|_{w=w^{t+1}} \tag{10}$$

where,
a = Dynamic factor, produced random among (0, 1)
η = Learning rate
t = Iterative steps
w^t = The weight matrix
w^{t+1} = The weight matrix of next generation

RESULTS AND DISCUSSION

Description of the constraints set: In network-based food product collaborative design, data are exchanged crossing department and platform. A prerequisite for conflict detection is a uniform expression of constraints (Gopalakrishnan and Kosanovic, 2015). The powerful ability of XML in describing and presenting data has been recognized as the standard for electronic data interchange in multi-disciplinary domains (Liu *et al.*,
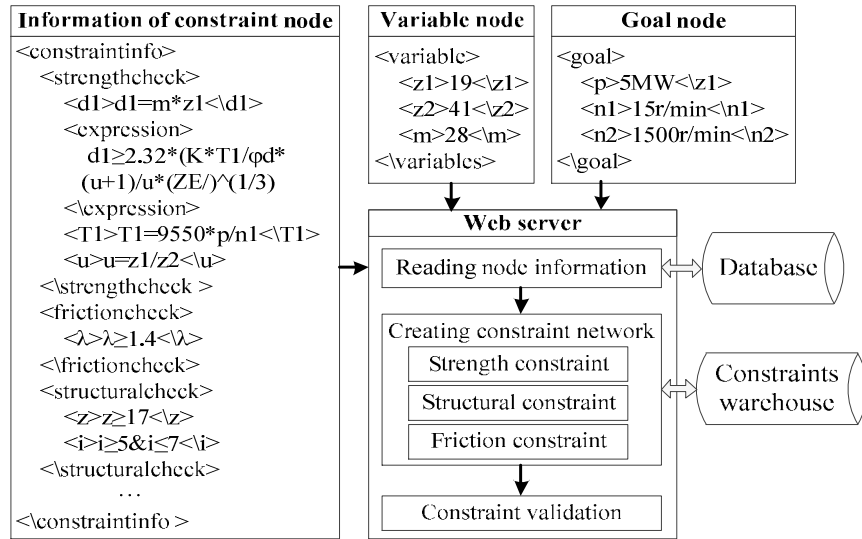
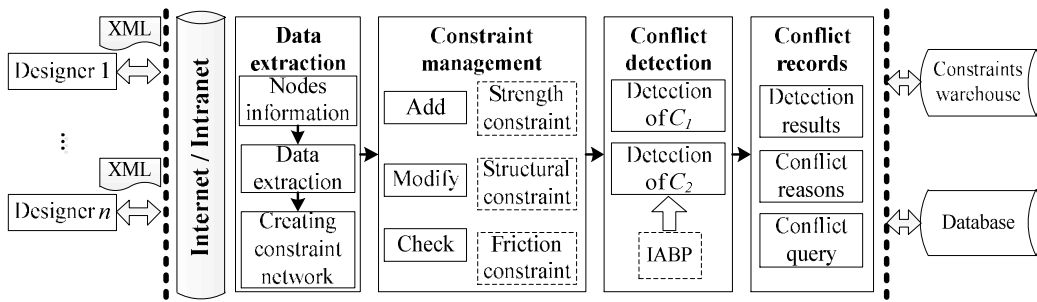Fig. 6: Detection process of constraint based on XML

Fig. 7: Architecture of conflict detection system

2005; Huang *et al*., 2004). In this study, we express the constraints in XML. Considering the characteristics of hierarchical constraint network, design variables, goals and constraints are described by XML and submitted to the Web server by the data format of XML. Figure 6 shows the description of constraints based on XML and its detection process.

The set of constraints based on XML is a document with tree structure, which contains elements, attributes and texts. According to the corresponding between node names and fields of SQL Server, design variables and goals are written into database (Haw and Lee, 2009). If a node contains child nodes, values will be mapped onto the sub-table and the child table and the parent table are associated by the primary key and ID. A hierarchical constraint network can be built through the constraints information and saved to the database. Constraints relationships are validated to determine whether conflicts have occurred.

Design of system architecture: The conflict detection system uses three-tier C/S architecture, shown in Fig. 7. Designers access Web server via Internet/Intranet. The system automatically detects conflicts and parameters

and results of detection are saved into the database as a repository.

Client layer: Designers exchange data from Web server through the client with the form of XML documents, including the design variables, the design goals and constraints, etc.

Web server layer: There are four sub modules, including data extraction, constraint management, conflict detection and records. Data extraction module creates the constraints relationships of the set C1 by reading the XML document and saves the design variables and design goals and other information into the database. Constraint management module manages the set of constraints by adding, modifying and checking the constraints from the aspect of structural constraint, strength constraint, friction constraint, etc. Conflict detection module detects the set C1 by constraints validation and the set C2 is detected by calling package GABP algorithm. Conflict records module feedbacks the results to the client and supports designers to query the conflicts.

Database layer: The system reads and stores the data, including design variables, goals, constraints and parameters trained by IABP.

CONCLUSION

From the respective of constraint satisfaction in food product collaborative design, this study divided constraints into a known set of constraints C1 and an unknown set of constraints set C2 and detected constraints, respectively. The set with known constraints was detected by interval propagation algorithm. At the same time, the BP neural network was proposed to detect the set with unknown constraints. IA was utilized to optimize the weights and thresholds of BP neural network. Simulation indicates that the IABP has better performance in convergent speed and global searching ability than GA. Compared with GABP and BP neural network, detection accuracy of IABP has been consumedly improved with the lowest error. On this basis, constraints were described by XML, so that computers can automatically recognize and establish the constraint network. Taking food product collaborative design of wind planetary gear train as an example, a conflict detection system in food product collaborative design has been developed. The conflict detection model is proved to be feasible and effective and provides a solution of conflict detection for food product collaborative design.

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