A Computational Model for Cultural Intelligence

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Abstract - Computational model can be designed with soft computing technologies which are capable of reasoning and learning in an uncertain and imprecise environment. However, in a real practical project, there are many difficult computational bottlenecks in need to break through when using these technologies. This research aims to invent a cultural intelligence computational model, which can process cultural intelligence soft data through the use of soft computing technologies. The purpose of this study is for individuals and organizations to solve the intercultural adaptation problems they may be faced with in a variety of authentic cross-cultural situations.

Keywords - Cultural Intelligence; Soft-Computing; Fuzzy Logic, Artificial Neural Network; Hybrid System

1 Introduction

Soft-computing is an advanced AI technology which can deal with uncertain, imprecise and incomplete information through an approach that is more human-like. Concerning the cultural domain, we live in an era of globalization where international activities between different cultures and intercultural communications and exchanges are becoming more common and are taking on much greater importance than ever before. Yet, because of cultural diversity, "Culture is more often a source of conflict than of synergy. Cultural differences are a nuisance at best and often a disaster" (Dr. Geert Hofstede). Moreover, cultural knowledge is generally represented by natural language, which is replete with vague and ambiguous terms, and it is difficult for traditional computing techniques to cope with these. In such a context, globalization and traditional computing techniques have encountered two major challenges: the first is how to adapt to cultural diversity, and the second is the treatment of soft data and human-like thinking.

Fortunately, research on cultural intelligence (CQ) [1] provides a new perspective and a new way to alleviate cultural issues that arise in such a globalized environment. The higher the CQ that people possess, the more effective their performance and adjustment will be in culturally diverse settings. CQ can also be improved by training the people involved in such settings. The most important point to consider is how to precisely evaluate CQ and provide relevant suggestions to improve it. However, current studies on CQ have used traditional methods to measure users’ CQ and have relied primarily on questionnaires to find solutions to CQ problems traditionally confined to the work of culture experts and researchers. The best way to enable non-expert users to make use of CQ knowledge at the present time is to computerize CQ. A great deal of CQ knowledge, however, is expressed as 'fuzzy data' and human decision making. Dealing effectively with these is beyond the scope of traditional computer technique, and research on CQ has never been empirically computerized to date.

These problems will be resolved by this research which will provide an effective solution through the invention of a CQ computational model.

2 Cultural Intelligence

CQ is defined as the ability to collect and process information, to form judgments, and to implement effective measures in order to adapt to a new cultural context [1]. Earley and Mosakowski [2] define CQ as a complementary intelligence form which may explain the capacity to adapt and face diversity, as well as the ability to operate in a new cultural setting. Earley and Mosakowski stress that people with a relatively high CQ level often appear at ease in new situations. They understand the subtleties of different cultures, so they can avoid or resolve conflicts early. Peterson interprets CQ in terms of its operation [3]. He believes that, for the concept of CQ, the definition of culture is compatible with the cultural values of Hofstede and their five main dimensions [4]. Peterson also describes CQ as the communicative capabilities which improve working environments. In other words, all workers have the ability to communicate efficiently with customers, partners and colleagues from different countries in order to maintain harmonious relationships. Brisling et al. define CQ as the level of success that people have when adapting to another culture [5]. Thomas describes CQ as the
capability to interact efficiently with people who are culturally different [6]. Johnson et al. define CQ as the effectiveness of an individual to integrate a set of knowledge, skills and personal qualities so as to work successfully with people from different cultures, both at home and abroad [7]. Finally, Ang et al. [8] define CQ as the conceptualization of a particular form of intelligence based on the ability of an individual to reason correctly in situations characterized by cultural diversity.

3 Cultural Intelligence Dimensions

Different researchers have different dimensional structures to measure CQ. Earley and Ang [1] are pioneers in the development of CQ concepts. They described the first structure of CQ in 2003 using a three-dimensional model: cognition, motivation and behavior. Thomas [9] advocates another tridimensional structure; he states that the structure of CQ should be based on the skills required for intercultural communication, that is to say, knowledge, vigilance and behavior. In these three dimensions, vigilance, which is the key to CQ, acts as a bridge connecting knowledge and behavior. Tan [10] believes that CQ has three main components: cultural strategic thinking, motivation, and behavior, and that CQ integrates these three components. Tan stresses the importance of behavior as being essential to CQ. If the first two parts are not converted into action, CQ is meaningless. Ang and Van Dyne [11] later refined the concept of Earley et al. to consist of four dimensions rather than three: metacognition, cognition, motivation and behavior. They paid special attention to how a culturally diverse environment works. This structure has been widely used in the following cultural research and studies. The four dimensions of CQ are described as follows:

- **Metacognitive CQ** refers to the cognitive ability of an individual to recognize and understand appropriate expectations in different cultural situations. It reflects the mental processes that an individual uses to acquire and understand cultural knowledge;
- **Cognitive CQ** is a person’s knowledge of the standards, practices and conventions in different cultures which he/she acquired from education and personal experiences;
- **Motivational CQ** refers to the motivation of an individual to adapt to different cultural situations. It demonstrates the individual’s ability to focus his/her attention and energy on learning and practicing in culturally diverse situations;
- **Behavioral CQ** is defined as an individual’s ability to communicate and behave with cultural sensitivity when interacting with people of different cultures. It represents a person’s ability to act and speak appropriately (i.e., use suitable language, tones, gestures and facial expressions) in a given culture.

4 Conceptual Model

The concept of CQ is for the first time extended in order to assess cross-cultural activities. One’s with a high CQ evaluation are expected to have a more effective performance in and adjustment to multicultural situations.

Sternberg et al. [12] state that general intelligence has four dimensions, i.e., Metacognition, Cognition, Motivation and Behavior. They consider the correlation between the four dimensions as an entity and take full account of their integrity because of their interdependence. CQ should also include and consider its four dimensions and their correlation. We agree that the four dimensions of CQ are critical factors that can help individuals, companies and organizations to overcome cross-cultural challenges. Thus, we believe that the diverse structures of CQ should be considered collectively in order to integrate the elements required to respond to the cultural knowledge acquired in cross-cultural activities. Therefore, we created a CQ conceptual model in order to complete the theories of CQ and the evaluation process required.

We present our model as a whole aggregate multidimensional construct by considering the following conditions: (1) the entire construct considers that the four CQ dimensions occupy the same important level in conceptualization; and (2) the four CQ dimensions form the construct. In sum, in our research we put forward the cognitive theory that the metacognitive CQ, cognitive CQ, motivational CQ and behavioral CQ are four interrelated components built into the CQ, and we integrate our theory into the model (see Fig.1).

![Figure 1. Cultural Intelligence Conceptual Model](image)

This conceptual model proposes a cyclical process of CQ evaluation in four stages, while respecting the correlation and interdependence between the four dimensions: (1) It observes the behaviors, promotes active thinking and drives individuals to adapt and revise their strategies in different cultural settings; (2) It acquires and understands the knowledge that can influence individuals’ thoughts and behaviors; (3) It considers the implications and emotions associated with cultural settings, and it drives efforts and energy toward effective functioning in a new culture; and (4) It transfers knowledge through verbal and nonverbal behaviors to the culturally diverse situations. This process enables us to identify the elements of the
global CQ so we may apply it as a whole, regardless of whether these dimensions are decision variables or other measurable parameters. In this process, we adopt a holistic approach that does not aim to reduce the model to its individual components.

5 Data and Knowledge Acquisition

Ang et al. [11] developed a self-assessment questionnaire which has 20 items that measure CQ. This questionnaire was used to collect data for studies on the test subjects regarding their capacity for cultural adaptation. The questionnaire is generally divided into four sections: metacognition, cognition, motivation and behavior. For example, one of the items is: "I am conscious of the cultural knowledge I use when I interact with people with different cultural backgrounds." Van Dyne et al. [13] developed a version of the questionnaire from the point of view of an observer. It is also based on the 20 items of Ang et al. [11] in order to measure CQ in individuals. The questionnaire was adapted from each item of the self-assessment questionnaire to reflect the assessment made by an observer rather than the user himself. As explained by Van Dyne et al. [13], these questionnaires allow for the effective assessment of CQ in practical applications.

We collected CQ knowledge by reviewing books, documents, manuals, papers, etc., and by interviewing cultural experts. One's CQ evaluations are often based on experts' intuition, common sense and experience. We clearly put forward that four CQ dimensions make up an integrated and interdependent body. A large number of fuzzy rules provided us with the means for modeling how experts measure one's CQ.

Among other potential applications, we identified the evaluation of CQ for application domains covered in our model. Thus, we adapted the self-assessment questionnaire of Ang et al. [11] and the observer questionnaire by Van Dyne et al. [13] to measure CQ.

6 Soft-Computing Technologies

The CQ generally has two types of data: the first type is associated with "hard" computing, which uses numbers, or crisp values; the second type is associated with "soft" computing, which operates with uncertain, incomplete and imprecise soft data. The second type is presented in a way that reflects human thinking. When we explain the cultural concept of cross-cultural activities, we usually use soft values represented by words rather than by crisp numbers. Traditional techniques, or "hard" computing, cannot treat CQ soft data. In order to enable computers to emulate human-like thinking and to model a human-like understanding of words in evaluation, we use a hybrid neuro-fuzzy technology to invent a CQ computational model. This soft-computing technology is capable of dealing with uncertain, imprecise and incomplete CQ soft data, which also possesses parallel computation and the learning abilities.

Fuzzy logic is introduced by Lotfi Zadeh who first realized the potential of soft computing and established the Berkeley Initiative in Soft Computing in March 1991[14]. The fuzzy logic technology is used in our model for three reasons. First, fuzzy logic is good for CQ knowledge, which is expressed in natural language that contains ambiguous and imprecise linguistic variables, such as "this person has high motivation" and "that person has lots of cultural knowledge." Second, fuzzy logic is well-suited to modeling human decision-making processes when dealing with "soft criteria." These processes are based on common sense and may contain vague and ambiguous terms. Third, fuzzy logic provides a wide range of cultural expressions that can be understood by computers.

Although the fuzzy logic technology has the ability and the means to understand natural language, it offers no mechanism for automatic rule acquisition and adjustment. The artificial neural network (ANN) offers learning mechanisms, which emulate human intelligence, in uncertain, incomplete and imprecise cultural settings. It presents viable solutions for processing incomplete and imprecise CQ information. The ANN can manage the new CQ data input and the generalization of acquired knowledge.

The hybrid neuro-fuzzy technology makes use of the advantages and power of fuzzy logic and the ANN. Fuzzy logic and the ANN are complementary paradigms. The hybrid technology represents the essence of our computational model.

7 Linguistic Variables and Fuzzy Rules

The idea of linguistic variables is one basis of the fuzzy set theory. A linguistic variable of fuzzy set theory is a fuzzy variable. For example, when we say "CQ is high," it means that the linguistic variable of CQ takes the linguistic value "high". Thus, our CQ linguistic variables are used in fuzzy rules in the model, for example:

Rule 1:

IF Metacognition is high AND Cognition is high AND Motivation is high AND Behavior is high

THEN CQ is high

The operations of CQ fuzzy sets used in our model are Intersection and Union [15]. For example, the fuzzy operation used to create the Intersection of two CQ fuzzy sets A and B is as follows:

\[
\mu_A \cap \mu_B(x) = \min \{\mu_A(x), \mu_B(x)\} = \mu_A(x) \cap \mu_B(x), \text{where} \ x \in X (1)
\]

The operation to form the fuzzy Union of two CQ fuzzy sets A and B is as follows:

\[
\mu_A \cup \mu_B(x) = \max \{\mu_A(x), \mu_B(x)\} = \mu_A(x) \cup \mu_B(x), \text{where} \ x \in X (2)
\]
8 Cultural Intelligence Computational Model

In this section, we describe the hybrid computational model in detail. The CQ computational model is based on our conceptual model (see section 4). The computational model is noteworthy because we use the four CQ dimensions as integrated and interdependent entities. Essentially, the model is a multi-layer neural network with the functional equivalency of a fuzzy inference process. The neuro-fuzzy network is composed of six layers in our computational model. It has four dimensions in the input layer and the CQ output layer, and four hidden layers that represent membership functions and CQ fuzzy rules. The model is shown in Fig. 2.

Layer 1 - Input: No calculation is made in this layer. Each of the 20 neurons corresponds to an input variable. These input values are transmitted directly to the next layer.

Layer 2 - Fuzzification: Each neuron corresponds to a linguistic label. To simplify the task, fuzzy linguistic variables used in our model are triangular membership functions (e.g., High, Medium and Low), associated with one of the input variables in Layer 1. We have 60 neurons in this layer.

Layer 3 - Fuzzy Rules: The output of a neuron at this layer is the fuzzy rules of CQ. For example, Neuron R1 represents Rule 1 and receives input from the neurons MC-Q1 (High) and MC-Q4 (High), etc.

Layer 4 - Fuzzification: In this layer, the neurons receive the membership degrees as the inputs which are produced from the fuzzy rules layer.

Layer 5 - Rule Unions (or consequence): This layer has two main tasks: 1) to combine the new precedent of rules; and 2) to determine the output level (High, Medium and Low) which belongs to the CQ linguistic variables. For example, R1 is the input of MC1 (High) and C1 (High), etc. It integrates the four dimensions of CQ to make a logical judgment in this layer by using 27 CQ rules.

Layer 6 - Combination and Defuzzification: This layer combines all the consequence rules and, lastly, computes the crisp output after Defuzzification. This layer has three neurons: CQ-High, CQ-Medium and CQ-Low. The Center of Gravity method is used to calculate the output. The single output after this layer is the precise CQ evaluation result. We apply, in this case, the triangle calculation in our model, which is the simplest calculation of the fuzzy set as shown in Fig. 3:

\[
y_{\text{Cultural Intelligence}} = \frac{1}{3} b_3 x + a_2 b_3 + \left( a_0 - \frac{1}{3} b_3 \right) b_2 x + b_2 x^2 + b_1 x^2 + b_1 x^3
\]

where \(a_2\) is the center and \(a_3\) is the end of the triangle. \(b_1\), \(b_2\) and \(b_3\) are the widths of fuzzy sets which correspond to CQ3-Low, CQ2-Medium and CQ1-High.

9 Supervised Learning

One of the main properties of the model is supervised learning, which has the ability to learn from CQ expert experiences and to improve performance by modifying the CQ rules through learning. Supervised learning involves cultural inputs and cultural outputs that are available to our
multilayer neuro-fuzzy network. The task of the network is to predict or adjust inputs to the desired outputs.

This multilayer neuro-fuzzy network can apply standard learning algorithms, such as back-propagation, to train it. The network offers a mechanism for automatic IF-THEN rule acquisition and adjustment. This mechanism is very useful, especially in situations where cultural experts are unable to verbalize the knowledge or problem-solving strategy they use.

The principle of the back-propagation algorithm in supervised learning in our model is that we provide the model with the final external CQ data that supervised learning requires; these data represent the results of a user’s evaluation. Each case contains the original input cultural data and the output data offered by CQ human experts to be produced by the model. The model compares actual output with the CQ experts’ data during the training process. If the actual output differs from the data given by experts in the training case, the model weights are modified. Fig. 4 shows first part (metacognitive dimension) of the Fig. 2 with three layers (input layer, hidden layer and output layer) as an example to illustrate how the neuro-fuzzy network learns by applying the back-propagation algorithm.

**Figure 4. Back-propagation in Cultural Intelligence Computational Model Learning**

MC-Q1 and MC-Q4 refer to neurons in the input layer; MC-Q1/MC-Q4 High, MC-Q1/MC-Q4 Medium and MC-Q1/MC-Q4 Low refer to neurons in the hidden layer; and R1, R2 and Rn refer to neurons in the output layer. We explain our model’s learning process theory in three steps as follows:

**Step 1 - Input Signals:** we input signals from MC-Q1 to MC-Q4 into the model; these signals are propagated through the neuro-fuzzy network from left to right, while the difference signals (or error signals) are propagated from right to left.

**Step 2 - Weights Training:** to propagate difference signals, we start at the output layer and work backward to the hidden layer. The difference signal at the output of neuron R1 at sequence s is calculated as follows:

$$D_{R1}(s) = y_{e, R1}(s) - y_{R1}(s) \quad (4)$$

where $y_{e, R1}(s)$ is the cultural experts’ desired output data of neuron R1 at iteration s. $D_{R1}(s)$ is the difference between the output $y_{R1}(s)$ and the experts’ desired output data at iteration s. For example, we use a forward procedure method to update the CQ rules’ weight $W_{MC-Q1HR1}$. Rule R1 for updating weight at the output layer at iteration s is defined as:

$$W_{MC-Q1HR1}(s + 1) = W_{MC-Q1HR1}(s) + \Delta W_{MC-Q1HR1}(s) \quad (5)$$

Following the above three-step learning procedure, we give a concrete example to show how the model obtains the desired value after learning. Suppose we have collected five people's answers as input data, and get five corresponding CQ evaluation results from the output of the model as: $y = [5, 6, 7, 3, 2]$. For any reason, the cultural experts gave five desired CQ output values as: $y_d = [7, 7, 6.5, 4.5, 7]$. We then used these five pairs of input data and the desired values to train the model. After nine epoch training processes, our new output from the model was: $y = [7, 7, 6.5, 4.5, 7]$, shown in Fig. 5.

**Figure 5. Learning Result in the Computational Model**
The model’s output quite accurately resembles the desired CQ values from the cultural experts, that is to say, the model has the ability to learn new CQ knowledge.

10 Conclusion

The achievement of this research is noteworthy because in the CQ domain, this study effectively deals with linguistic variables, soft data and human decision making based on a hybrid neuro-fuzzy technology, and it possesses parallel computation and the learning abilities of neural networks. At the same time, due to its powerfully designed functions, the model is very easy to extend to other application domains, such as integrating the Expatriation and Business Activities [16].

The other main contributions of our study are: 1) in the cognitive domain, it improves the application of CQ theories. The study focuses on modeling four CQ dimensions as an integrated and interdependent body. As a result, the theories are more complete, efficient and precise in their application. 2) In the application of soft-computing, it fills the gap between CQ and soft-computing. As a result, this innovative study provides the opportunity for new research topics and directions, and expands the range in the field of soft-computing.

11 References


