A Hybrid Intelligent System in Cultural Intelligence

Zhao Xin Wu and Li Zhou

Abstract 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. Researches on cultural intelligence supply a new perspective and a promising way to reduce intercultural conflicts or obstacles. To date, no research on cultural intelligence has been empirically computerized. This research aims to invent a cultural intelligence computational model and to implement the model in an expert system in order to process cultural intelligence soft data through the use of hybrid artificial intelligence technology. This intelligent system represents a breakthrough in the cultural intelligence and AI domains. The purpose of this research is to support individuals and organizations in solving the intercultural adaptation problems that they face in various authentic situations.

Keywords Cultural intelligence · Fuzzy logic · Artificial neural networks · Expert system · Hybrid intelligent technologies

1 Introduction

The globalization has increased dramatically. Culture can play a significant role in the success or failure of face-to-face encounters [1], and because of cultural diversity, "Culture is more often a source of conflict than of synergy. Cultural

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differences are a nuisance at best and often a disaster" (Dr. Geert Hofstede). Confronted with cultural diversity, some individuals and organizations successfully adapt themselves to a new cultural environment, but others do not. Why is the decisive factor for these completely different results? How a good decision can be made in different cultural environment? What skills can be improved for cultural adaptation? In recent years, cultural intelligence (CQ) has been presented as a new phenomenon to answer these questions in certain ways. However, current studies relative to CQ are currently treated at the manual level. Moreover, cultural knowledge is generally represented by natural language, in 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, for human beings, how to adapt to cultural diversity, and the second is, for computers, the processing of "soft data" and the representation of human-like thinking.

The main focus of this research attempts to give effective solutions for the problems mentioned above. There are three goals of this study: (1) To help individuals and companies in decision-making processes that involve cultural affairs. (2) To improve use a specific form of intelligence based on an individual's capacity to understand, to reason correctly, and to adapt to culturally diversified situations [2]. (3) To facilitate the work of researchers and to better equip them in their CQ studies.

2 Cultural Intelligence and Its Dimensions

Cultural Intelligence has been referred to as the acronym CQ. Earler and Ang [3] present CQ as a reflection of people's ability to collect and process information, to form judgments, and to implement effective measures in order to adapt to a new cultural context. Earley and Mosakowski [4] later redefined is 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. Brisling and Worthley [5] define the CQ as the level of success that people have when adapting to another culture. Thomas and Inkson [6] describes CQ as the capability to interact efficiently with people who are culturally different. Johnson et al. [7] 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 and countries.

Different researchers have different dimensional structures to measure CQ. Earley and Ang [3] describe the first structure of CQ by three dimensions: cognition, motivation and behavior. While Thomas and Inkson advocate another tridimensional structure. They state that the structure of CQ should be based on the skills required for intercultural communication, that is to say, knowledge, vigilance and behavior [6]. In these three dimensions, vigilance, which is the key to CQ, acts as a bridge connecting knowledge and behavior. Tan [8] believes that CQ has three main components: (1) cultural strategic thinking; (2) motivational; and (3) behavioral. CQ integrates these three components. Tan stressed the importance of behavior as being essential to CQ. If the actions in the first two parts are not converted into action, CQ is meaningless.

Ang and Van Dyne [9] suggest a CQ structure with four dimensions rather than three. This structure has been widely used in the following cultural researches and studies. The four dimensions of CQ are described as following:

- *Metacognition* 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.
- *Cognition* is a person's knowledge of the standards, practices and conventions in different cultures which he/she acquired from education and personal experiences.
- *Motivation* 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.
- *Behavior* 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 [9].

Although studies of CQ structures have made some progress in the three-dimensional and four-dimensional structures, they are not always conclusive. One of the most potentially contentious issues is whether the structure should or should not include a metacognitive CQ dimension. Moreover, apart from the three and four dimensions identified in the structures, are there any other dimensions or important elements to consider in CQ structures? To answer these questions, there is a need for further theoretical and empirical researches.

3 Cultural Intelligence Computational Model

3.1 Data and Knowledge Acquisition

Kon et al. [10], Ang et al. [2, 11] developed a self-assessment questionnaire which has 20 questions that measure CQ. This questionnaire was used to collect data for studies on the capabilities of the test subjects regarding their cultural adaptation capacity. This questionnaire is generally divided into four sections: metacognitive (four questions), cognitive (six questions), motivational (five questions) and behavioral (five questions). For example, one of the questions from metacognitive section is "I am conscious of the cultural knowledge I use when I interacting with people with different cultural backgrounds." Van Dyne et al. [12] developed a version of the questionnaire from the point of view of an observer. It is also based on the 20 questions of Ang et al. [2, 11] in order to measure the CQ of individuals. The questionnaire was adapted from each question of the self-assessment questionnaire to reflect the assessment made by an observer rather than the user himself. For example, the question of the questionnaire shown above changes from: "I am conscious of the cultural knowledge I use when …" to "This person is conscious of cultural knowledge he/she uses when …." As explained by Van Dyne et al. [12], these questionnaires allow for the effective assessment of CQ in practical applications. We therefore adapted the self-assessment questionnaire of Ang and Van Dyne [2], along with the observer questionnaire by Van Dyne et al. [12] to measure CQ in order to integrate the evaluation functions offered by our system. Thus, the user can be evaluated and proper recommendations can be offered by the system.

3.2 Applying Hybrid Artificial Intelligent Technology to Computational Model

We used the hybrid neuro-fuzzy technology to design this model. This hybrid technology makes use of the advantages and power of fuzzy logic and Artificial Neural Network (ANN), which are complementary paradigms. (1) fuzzy logic technology is used for three reasons. First, the CQ variables, which are ambiguous and imprecise, such as "this person has low motivation" and "that action is highly risky because of this religion." Second, fuzzy logic is particularly well-suited for modeling human decision-making when dealing with "soft data," which come from common sense, as well as vague and ambiguous terms. Third, fuzzy logic provides a wide range of expressions that can be understood by computers. (2) ANN: Although the fuzzy logic technology has the ability and the means of understanding culturally natural language, it offers no mechanism for automatic rule acquisition and adjustment. The ANN is a good solution for processing incomplete cultural information. The ANN can incorporate new cultural data input with the generalization of acquired knowledge. The hybrid neuro-fuzzy technology which can process CQ "soft data" represents the essence of our computational model.

Modeling is an essential step. Our computational model describes in an abstract way the entity of the system and the problematic to solve in our research in order to understand better them. The model includes a highly detailed plan so as to take into consideration the general layout of the system. The model based on the four dimensional structure of Ang and Van Dyne [9] (see Sect. 2). The model is noteworthy because we use the four CQ dimensions as integrated and interdependent entities. This model represents a comprehensive overview of the various aspects of CQ researches. Our model 'filters' the non-essential details of information. The main three parts of our model are shown in Fig. 1.

- *Input unit* presents information (questionnaires) which expresses the answers of the user via the input of the user interface;
- *Filter and Classifier module* takes the inputted information, classifies it, and filters what is not useful for analysis in the next steps;

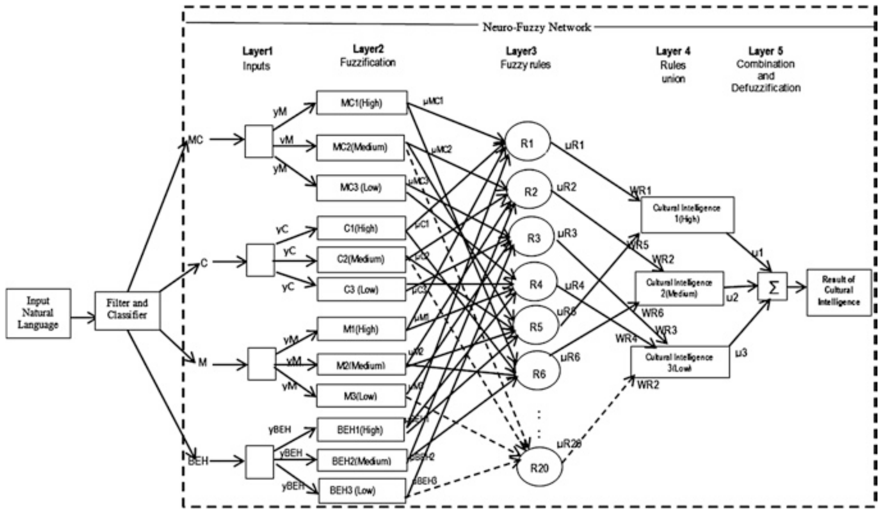
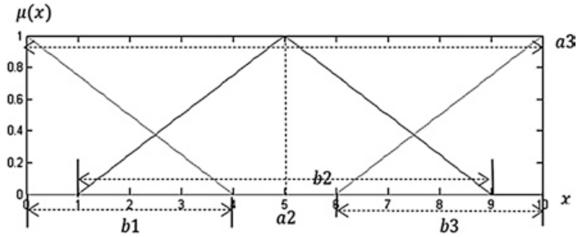


Fig. 1 CQ computational model

- *Neuro-Fuzzy Network* is a neural network with fuzzy inference model capabilities. The system can be trained to develop IF-THEN cultural fuzzy rules and determine membership functions for input and output variables. This unit has four inputs: metacognition (MC), cognition (C), motivation (M) and behavior (BEH), and it has one output: CQ.

Layer 1—*Inputs*: No calculation is made in this layer. Each neuron 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 (e.g., high, medium and low) associated with one of the input variables in layer 1. In other words, the connection of the output, representing the inclusion value which specifies the degree to which the four input values belong to the neuron's fuzzy set, is calculated in this layer.
Layer 3—*Fuzzy Rule*: The output of a neuron at level 3 is the fuzzy rules of CQ. Each neuron corresponds to one fuzzy rule. The neuron receives as input from the Fuzzification neurons. Neuron R1 represents Rule 1 and receives input from the neurons MC1 (High) and C1 (High). The weights (WR1 to WRn) between layers 3 and 4 are the normalized degree of confidence of the corresponding fuzzy rules. These weights are adjusted when the model is trained.
Layer 4—*Rule Unions* (or consequence): This neuron 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, μR1, μR5 are the inputs of CQ1 (High), and $\mu 1^{(4)}$ is the output of neuron CQ1 (High).
Layer 5—*Combination and Defuzzification*: This neuron combines all the consequence rules and, lastly, computes the crisp output after Defuzzification. The composition method "sum-product" [13] is used. This method represents a shortcut of

Fig. 2 General CQ Fuzzy sets



the Mamdani-style inference calculation. It computes the outputs of the membership functions defined by the weighted average of their centroids. The calculation formula of weighted average of the centroids of the clipped fuzzy sets CQ3 (Low), 2 (Medium) and 1 (High) are calculated as shown in Fig. 2.

$$y(CQ) = \frac{\frac{1}{3}b_1^2\mu 1 + a_2 b_2 \mu 2 + \left(a_3 - \frac{1}{3}b_3\right) b_3 \mu 3}{b_1\mu 1 + b_2\mu 2 + b_3\mu 3} \tag{1}$$

where $a2$ is the center and $a3$ is the end of the triangle. $b1$, $b2$ and $b3$ are the widths of fuzzy sets which correspond with CQ 3, 2 and 1.

4 Supervised Learning

One of the main properties of the model is supervised learning, which has the ability to learn from cultural 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 CQ 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. Figure 3 shows two parts (metacognitive and cognitive dimensions) of the Fig. 1 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

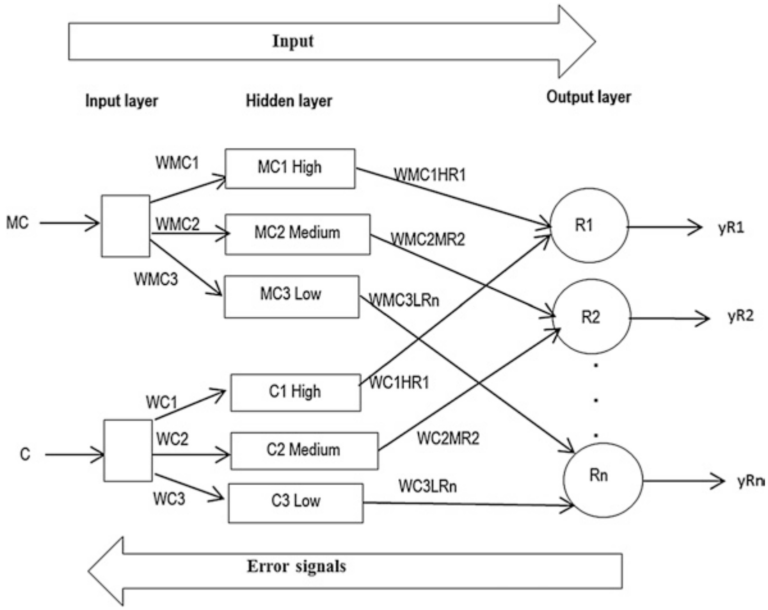


Fig. 3 Back-propagation in CQ computational model learning

algorithm. *MC* and *C* refer to neurons in the input layer; *MC1/C1 High*, *MC2/C2 Medium* and *MC3/C3 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* to *C* 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:

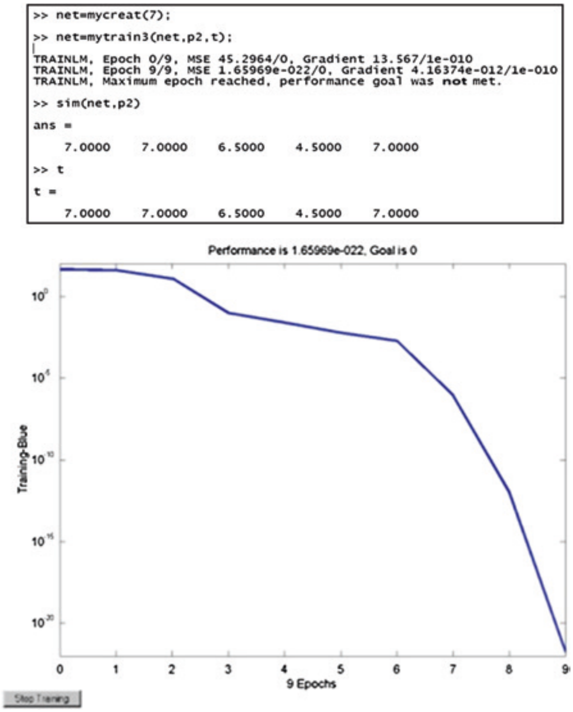
$$\mathrm{D_{R1}(s) = y_{e,R1}(s) - y_{R1}(s)} \tag{2}$$

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_{MC1HR1}(MC1 High) Rule *R1* for updating weight at the output layer at iteration *S* is defined as:

$$\mathrm{W_{MC1HR1}(s+1) = W_{MC1HR1}(s) + \Delta W_{MC1HR1}(s)} \tag{3}$$

Step 3 **Iteration**: We increase iteration *S* by one and repeat the process until the pre-set difference criterion is satisfied.

Fig. 4 Learning result in the computational model



Following the above three-step learning procedure, we give a concrete example to demonstrate how the model obtains the desired value after learning, shown in Fig. 4. 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: yd = [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].

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.

5 Implementing the Model in an Intelligent System

We would like the system, first, to be capable of acquiring, extracting and analyzing the new CQ knowledge of experts, and second, to serve as an efficient team comprised of top CQ experts, able to provide both recommendations and explanations to users whenever required in culturally diverse settings. Hence, we implemented the computational model in an expert system, called Cultural Intelligence

Evaluation Expert System (CQEES). Figure 5 shows the structure of the CQEES. The CQEES structure includes four main modules:

- *The CQ Computational Model* contains CQ knowledge that is useful for solving CQ problems. The soft-computing technology used in this model enables the system to reason and learn in an uncertain and imprecise CQ setting. It supports all the evaluation steps in the system. This module connects with the *Training Data Database*. The *Training Data Database* are sets of training examples used for training the neuro-fuzzy network during the learning phase.
- *The Cultural Intelligence Rules* examine the CQ knowledge base, which is represented by the trained network, and produce rules which are implicitly built into and incorporated in the network.

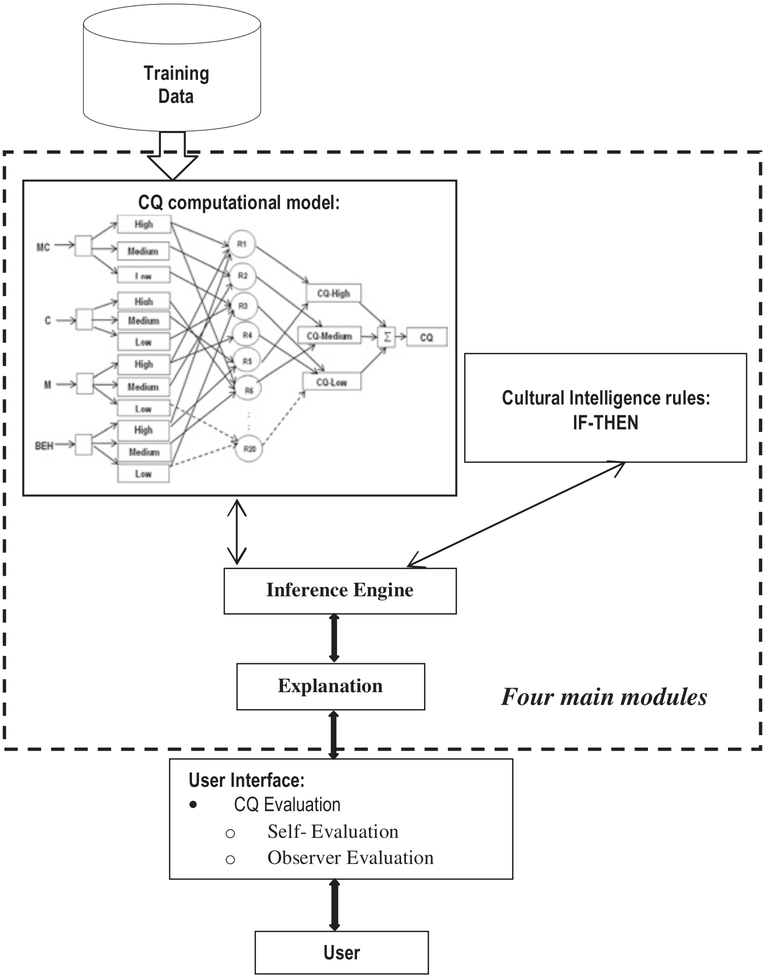


Fig. 5 Structure of CQEES

- *The Inference Engine* controls the flow of information in the system and initiates inference reasoning from the computational model. It also concludes when the system has reached a solution.
- *The Explanation module* explains to the user why and how the CQEES reached the specific CQ evaluation results. These explanations include the conclusion, advice and other facts required for deep reasoning.

The computational model and CQEES are validated and confirmed by evaluations conducted by several cultural experts. The experts simulated some real world problems. These validations ultimately reflect the consistency between the real world and the artificial intelligent system. Based on the results of the validation, users can get two evaluations (self- and observer evaluations) using the 20-item questionnaires (see the interface of the system prototype in Fig. 6).

The CQ evaluation process in the CQEES, first of all, receives the input data from the 20 items of the questionnaire. The system then analyzes and treats these data specifically by applying the strategies of CQ human experts. At the end, the system gives the result of the CQ evaluation and provides suggestions for users who want to follow the CQ training.

Figure 7 illustrates the CQEES as a black box where the input data corresponds to the answers to the 20 items. The output is the evaluation result with explanations to the users.

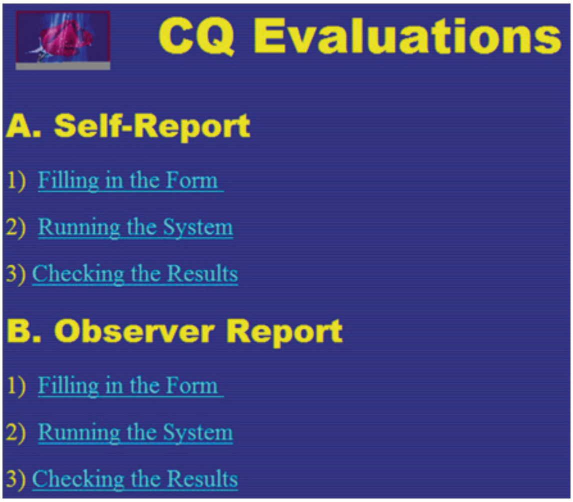


Fig. 6 Interface of CQEES prototype

Fig. 7 Input and output of CQEES

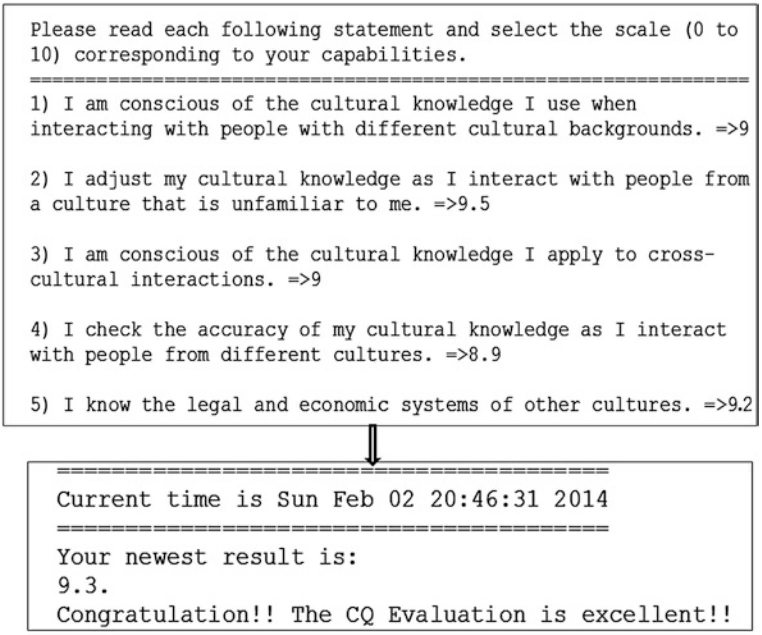


Fig. 8 Self-evaluation result in CQEES (scores higher than 8)

For example, two different results of the self-evaluation questionnaire that evaluate the user's CQ are presented in the CQEES as follows:

Result 1: After inputting the answers to the 20 items in the CQEES, the system provides the feedback. If a user's evaluation achieves a high score (e.g.: more than 8), the system shows the following message in Fig. 8
Result 2: When the evaluation results are below 6, the system accordingly gives useful suggestions for personal self-development as required. This process permits the system to evaluate users so as to identify their problems in the CQ domain and then offers several precise recommendations to users based on the results of the evaluation. Moreover, the system uses natural language to give users recommendations in order to provide them with a stress-free and friendly evaluation. The CQEES presents some recommendations in Fig. 9

The evaluation result shows that the CQEES allows for improved interactions and for more effective aid to users. The evaluation result clarifies and defines the exact problem of concern to the users; indeed, the CQEES could be used in self-awareness training programs. The system provides important insights on personal capabilities, as well as information on the user's own CQ in situations where cultural diversity is of primary importance. This point is particular importance in modern learning theories. Organizations could also use the CQEES (both self- and observer evaluations) to evaluate and train employees so that the latter may function more effectively in such situations.

```
Please read each following statement and select the scale (0 to
10) corresponding to your capabilities.
=================================================================
1) I am conscious of the cultural knowledge I use when
interacting with people with different cultural backgrounds. =>9

2) I adjust my cultural knowledge as I interact with people from
a culture that is unfamiliar to me. =>9.5

3) I am conscious of the cultural knowledge I apply to cross-
cultural interactions. =>9

4) I check the accuracy of my cultural knowledge as I interact
with people from different cultures. =>8.9

5) I know the legal and economic systems of other cultures. =>9.2
```

```
========================================
Current time is Sun Feb 02 20:27:21 2014
========================================
Your newest result is:
5.5.
*****************
In future training, the system suggests you that
you pay more attention to the following aspects
to improve your CQ ability:

A)In Motivation
 1) Deal with the stresses of adjusting to a culture that is new
to you.

B)In Cognition
 1) The arts and crafts of other cultures.
 2) The rules for expressing non-verbal behaviors in other
cultures.

C)In Behavior
 1) Changing verbal behavior <e.g., accent, tone> when a cross-
cultural interaction requires it.

D)In Metacognition
 1) The cultural knowledge when interacting with people with
different cultural backgrounds.
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Fig. 9 Self-evaluation result in CQEES (scores lower than 6)

The CQEES serves as an efficient team comprised of top CQ experts who work continuously with individuals and organizations that wish to have an evaluation or insights on how to improve their effectiveness in culturally diverse settings.

6 Conclusion

CQ is defined as the capacity to function effectively in cultural diversity. 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. From a practical perspective, first, the system is able to evaluate trainees and provide them specific recommendations. It is also able to dynamically adapt to the CQ capacity of trainees. Second, this system is open in the sense that it can provide a standard interface that can facilitate further development. Third, the CQEES is also extensible, both in terms of the system concept model and the system implementation. Fourth, this system has the potential to work as a training extension agent in order to integrate it into another existing intelligent system. Fifth, due to its powerfully designed functions, this system is very easy to extend to other application domains, such as Expatriation and Business Activities [14]. As a result of its high CQ capabilities, the system can not only use its knowledge to train people, but also to work as a CQ decision-making support system to help individuals and organizations take cultural decisions in cross cultural activities.

The contribution of our research, first, fills that gap between CQ and AI. Second, it improves the application of CQ theories in the cognitive domain. The research focuses on modeling four CQ dimensions as an integrated and interdependent body. As a result, the theories should be more complete, more efficient, and more precise in their applications. Third, we have made progress in the domain of AI by computerizing CQ. As a result, new research topics and directions have arisen, and the range of computational intelligence possibilities has been expanded. Fourth, our research is groundbreaking as it simplifies the work of the researchers by freeing them of heavy, complex, repetitive tasks, normally carried out manually in the process of CQ studies.

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