A Synergic Neuro-Fuzzy Evaluation System in Cultural Intelligence

Zhao Xin WU¹, Jacqueline BOURDEAU², Roger NKAMBOU³

 ^{1,3} Computer Science Department, University of Quebec in Montreal PO Box 8888, Downtown, Montreal, QC, H3C 3P8, Canada wu.zhao_xin@courrier.uqam.ca; nkambou.roger@uqam.ca
 ² LICEF, Télé-Université, 100 Sherbrooke, O., Montreal, QC, H2X 3P2, Canada Jacqueline.bourdeau@licef.ca

Abstract. In today's age of globalization, cultural awareness has become a challenge for designers of tutoring systems to include the cultural dimension in the tutoring strategy and in the learning environment. Nevertheless, cultural awareness is also a domain to be learned by a student, and a competency that can be assessed. Research on cultural intelligence has provided a new perspective and presented a new way to alleviate issues arising from cross-cultural education. To date, no research on cultural intelligence has been empirically computerized with soft-computing technology. This research aims to invent a cultural intelligence computational model and to implement the model in an expert system through the use of artificial intelligence technology. The purpose of this study is to provide intercultural training for individuals to solve the intercultural adaptation problems they may be faced with in a variety of authentic cross-cultural situations.

Keywords: Cultural Intelligence, Fuzzy Logic, Artificial Neural Network, Expert System, Hybrid Technology

1 Introduction

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. Cultural awareness has become a challenge for designers of tutoring systems to include the cultural dimension in the tutoring strategy and in the learning environment. Nevertheless, cultural awareness is also a domain to be learned by a student, and a competency that can be assessed. Culture is an ill-defined domain [1]. Culture can play a significant role in the success or failure of face-to face encounters [2, 3], and 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, 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. In the field of Culturally-Aware Tutoring Systems (CATS), several efforts have been conducted towards a declarative knowledge representation of culture as a phenomenon in order to foster and assess the awareness of cultural differences among human beings, and of their impact on behaviour and attitudes [1, 2, 3, 4]. The problem addressed in this paper is not how learning environments can adapt to culture, but how to assess human beings in terms of their level of cultural awareness, and make recommendations for their training.

We became interested in the research on cultural intelligence, which provides a new perspective and a new way to alleviate cultural issues that arise in globalized environment. Following Earley and Ang [4], Cultural Intelligence is thereafter called Cultural Quotient (CQ). The higher the CQ that people possess, the more effective their performance and adjustment will be in culturally diverse settings [5]. 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'. Dealing effectively with these is beyond the scope of traditional computer technique. Research on CQ has never been empirically computerized to date. Additionally, in reference to cultural aware intelligent systems, researches concerning the Artificial Neural Network (ANN) and fuzzy logic technologies to CQ have not been used before. Up until now, application of this soft-computing technology to CQ has not been found in literature reviews.

This research attempts to provide effective solutions for the abovementioned problems. Based on advanced AI technologies, a CQ computational model is invented and implemented in an expert system. This system has successfully manipulated linguistic variables, soft data and human-like reasoning.

2 What is Cultural Intelligence?

The definition of CQ relies upon an understanding and an interpretation of a definition of 'culture' itself. According to Hofstede [6], culture is '*The collec*-

tive programming of the mind which distinguishes the members of a human group from another'. Sperber claims that culture can be understood as an epidemiology of representations [7], Kroeber and Kluckhohn [8], in their article 'Culture: A Critical Review of Concepts and Definitions', inventoried a list of over 200 different definitions for the word 'culture'. Moreover, when referring to someone's ability to understand and adapt to different cultures, some authors use the term 'Inter- cultural Sensitivity' [9]. We adopted the definition proposed by Earley and Ang [4], who define CQ 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. Earley and Mosakowski [10] define CO 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 [11]. He believes that, for the concept of CQ, the definition of culture is compatible with the cultural values of Hofstede. 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 [12]. Thomas describes CQ as the capability to interact efficiently with people who are culturally different [13]. 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 [14]. Finally, Ang et al. [15] 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. Ang and Van Dyne [18] paid special attention to how a culturally diverse environment works. They refined the concept of Earley et al. [4] to consist of four dimensions of CQ: metacognition, cognition, motivation and behavior. This structure has been widely used in the following cultural research and studies.

3 Data and Knowledge Acquisition in the Application Domain

We collected data and CQ knowledge by reviewing books, documents, manuals, papers, etc., and by interviewing cultural experts. Among other potential applications, we identified the evaluation of CQ for application domains covered in our system.

Ang et al. [16] developed a self-assessment questionnaire which has 20 items that measure CQ. This questionnaire was validated across samples (n=1564), time, countries and method of measurements. 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. [17] 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. [16] in order to measure CQ in individuals. The questionnaire was adapted from each item of the selfassessment questionnaire to reflect the assessment made by an observer rather than the user himself. As explained by Van Dyne et al. [17], these questionnaires allow for the effective assessment of CQ by cultural experts in practical applications. It is difficult to evaluate users only by these questionnaires without any cultural experts present. Thus, we adapted the self-assessment questionnaire and the observer questionnaire to measure CQ in order to integrate the CQ experts' knowledge, for the purpose of evaluation and recommendation functions offered by our system. Users can therefore be evaluated, and appropriate suggestions can be offered by the system.

4 Cultural Intelligence Computational Model

When processed by humans through questionnaires, 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, 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.

The hybrid neuro-fuzzy technology makes use of the advantages and power of fuzzy logic and the ANN. The hybrid technology represents the essence of our computational model. The CQ computational model is based on the four-dimensional structure of Ang et al. [16]. The model is noteworthy because we clearly put forward and use that four CQ dimensions make up an integrated and interdependent entities. Essentially, the computational model is a multi-layer neural network with the functional equivalency of a fuzzy inference process. This neural network is not a simple neural network due to all of the cultural rules embodied in these structure nodes. The neuro-fuzzy network is composed of six layers in our computational model. The model is shown in Fig. 1. This hybrid computational model has 20 inputs which represent the 20 items of the questionnaires to measure CQ: the metacognitive dimension (MC) has four items, the cognitive dimension (C) contains six items, the motivational dimension (M) includes five items and the behavioral dimension (BEH) consists of five items and has one output: CQ.

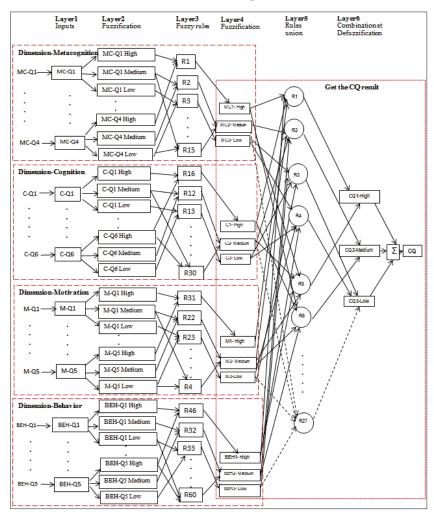


Fig. 1. Computational Model of Cultural Intelligence

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. 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.

This multilayer neuro-fuzzy network can apply standard learning algorithms (such as back-propagation) to train it. This mechanism is very useful, especially in those situations where cultural experts are unable to verbalize which knowledge or problem-solving strategy they use. To illustrate how the computational model learns, consider an example from this model shown in Fig. 2.

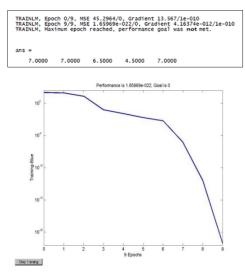


Fig. 2. Learning in the Computational Model

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 corresponds to the CQ values provided by the cultural experts. In the future, the system should be trained with big data and calibrated consequently.

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 CQES (Cultural Intelligence Evaluation System). Fig. 3 shows the structure of the CQES.

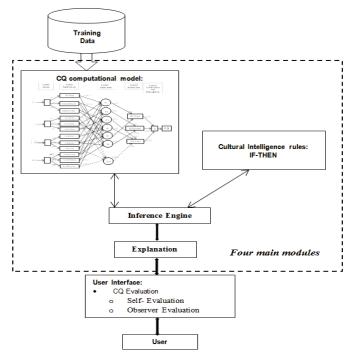


Fig. 3. Structure of CQES

The CQES structure includes four main modules: 1) 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. 2) 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. 3) 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. 4) The Explanation explains to the user why and how the CQES reached the specific CO evaluation results. These explanations include the conclusion, advice and other facts required for deep reasoning. Therefore, the following details explain how users can get two evaluations (self and observer evaluations) using the 20-item questionnaires (see the interface of the CQES in Fig. 4).



Fig. 4. Interface of CQES

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

Result 1: After inputting the answers to the 20 items in the CQES, 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:

```
Current time is Fri Jan 04 18:12:02 2013

Your newest result is :

9.5.

Congratulations! The CQ Evaluation is excellent !!
```

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 lan-

guage to give users recommendations in order to provide them with a stressfree and friendly evaluation. The CQES presents some recommendations as follows:



Organizations could also use the CQES (both self- and observer evaluations) to evaluate and train employees so that the latter may function more effectively in such situations. We envisage that CQES could effectively be integrated in a CATS to offer training in culture intelligence based on the assessment provided by CQES.

6 Conclusion

This research is original and attempts to give a productive solution by replacing or supporting CQ experts with computers for assessing and provide recommendations for training. This innovative research has managed to computerize the underlying principles of CQ in order to help individuals to improve their ability to adapt to a new culture.

The main contributions of this research are: inventing a CQ computational model and implementing the model in an expert system called CQES. As a 'culturally aware' intelligent system, the CQES can be used to train individuals in CQ training by providing them with evaluation, and specific suggestions to improve their weaknesses in the corresponding area. This point is of particular importance in modern learning theories.

7 References

1. Blanchard, E. G., Mizoguchi, R., Lajoie, S. P. (2010). Structuring the cultural domain with an upper ontology of culture. Handbook of research on culturally aware information technology: Perspectives and models, IGI Global, Hershey PA.

- Lane, H. C., Hays, M. J (2008). Getting down to business: Teaching cross-cultural social interaction skills in a serious game. Culturally-Aware Tutoring Systems, ITS 2008, Montreal, Canada, June 23-27
- Lewis Johnson, W., Rickel, J. W., Lester, J. C. (2000). Animated pedagogical agents: Face-to-face interaction in interactive learning environments. International Journal of Artificial intelligence in education 11.1. pp.47-78
- Earley, P.C., Ang, S (2003). Cultural intelligence: Individual interactions across cultures. Stanford, CA: Stanford University Press.
- Wu, Z. X., Nkambou, R., Bourdeau, J. (2012). The Application of AI to Cultural Intelligence. The 2012 World Congress in Computer Science, Computer Engineering and Applied Computing, ICAI 2012, The International Conference on Artificial Intelligence, Las Vegas, U.S.A.
- Hofstede, G. (1980). Culture's consequences: International differences in work-related values. London: Sage Publications.
- 7. Sperber, D. (1996). Explaining culture: A naturalistic approach, Oxford: Blackwell.
- 8. Kroeber, A. L., Kluckhohn, C., Untereiner, W., Meyer, A. G. (1952). Culture: A critical review of concepts and definitions (Vol. 47, No. 1). New York: Vintage Books.
- Bennett, J. M., Bennett, M. J. (2004). Developing Inter-cultural Sensitivity: An Integrative Approach to Global and Domestic Diversity. In Dan Landis, Janet M. Bennett, & Milton J. Bennett (Eds.), Handbook of Intercultural Training, 3rd ed., pp. 147–165
- Earley, P. C., Mosakowski, E. (2004). Cultural Intelligence. Harvard Business Review, 82, pp.139–146
- 11. Peterson, B. (2004). Cultural intelligence: A guide to working with people from other cultures. Yarmouth, ME: Intercultural Press.
- 12. Brisling, R., Worthley, R., MacNab. (2006). Cultural Intelligence: understanding behaviors that serve people's goals. Group and organization management.
- Thomas, D. C., Inkson, K. (2005). Cultural Intelligence People Skills for a Global Workforce. Consulting to Management, vol. 16 (1). March. pp. 5-9
- Johnson, J. P., Lenartowicz, T., Apud, S. (2006) Cross-cultural Competence in International Business: Toward a Definition and a Model. Journal of International Business Studies, vol. 37. pp. 525–543
- Ang, S., Van Dyne, L. (2008). Conceptualization of Cultural Intelligence. Handbook on cultural intelligence: Theory, measurement and applications, Chapter I, pp.1-15. Armonk, NY: M.E. Sharpe.
- Ang, S., Van Dyne, L. (2010). Handbook of Cultural Intelligence. 1st ed. M.E. Sharpe. Armonk.
- Van Dyne, L., Ang, S., Koh, C. (2008). Development and Validation of the CQS: The cultural intelligence scale. Handbook of Cultural Intelligence. 1st ed. M.E. Sharpe, Armonk.