S. L. Wong et al. (Eds.) (2010). Proceedings of the 18th International Conference on Computers in Education. Putrajaya, Malaysia: Asia-Pacific Society for Computers in Education.

A Computerized Approach to Group Discussion and Decision Making

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Abstract: Today, collaborative learning in high-tech institutions is not limited to supply of material by instructors and merely its consumption by students. Instead, learning is viewed as a cooperative task involving group discussions and analysis of the supplied information. Group discussion takes different forms starting from primary school activities till collaborative research and development projects in universities. On the basis of this idea, this paper introduces a practical computerized model for analyzing different viewpoints of a group of individuals on a specific decision problem or a single fact of knowledge. The results are presented using an example of a decision problem including 10 factors where 3 decision makers discuss to reach a consensus over the finalized values of the factors.

Keywords: Group Decision Making; Collaborative Learning

Introduction

Soft computing is used for modeling dynamical and real-life systems with increasingly trusted computer analysis. It has been utilized by decision makers in variety of cumbersome situations. Different methodologies have emerged, including fuzzy logic, artificial neural networks, and heuristic search such as genetic algorithm, particle swarm optimization, etc. Inspired by biological neural connections in human brain, the artificial neural network (ANN) has been of a higher interest among computer scientists. However, with the advent of the fuzzy logic (FL), semantic definition of real-life problems using linguistic terms has become increasingly attractive. Fuzzy cognitive map (FCM) [1, 2] is a graph-like soft computing tool with the benefit of both recurrent (graph-like) neural network, and fuzzy logic. FCM is made up from nodes (factors), and edges (effects of factors). Therefore, the factors can influence each other with respect to the extent (positive or negative intensity) of the effects among them. Experts define the factors and their effects in a given problem and then execute the developed FCM for obtaining decision results, i.e., finalized values of the factors. Usually, decision making involves N_{in} input factors (dependent or independent), and N_{out} decision factors which N_{in} affect N_{out} [3]. However, in some situations these may overlap or exchange role. This paper, examines a decision problem using capabilities of the FCM while incorporating the concept of group discussion. It must be noted that no role (input or output) is assigned to the factors since this paper only discusses the methodology of this technique through a generic example.

Group FCM Decision Modeling

Traditionally, there are two FCM computational models namely definition and incremental formulas [4]. Although FCMs can be trained for more robust decision making, i.e., by genetic algorithms (GA) [5, 6, 7] or Hebbian algorithms [8, 9, 10], however, still the basis of the inference (deriving outputs from inputs) is on either of the two standards frameworks: definition or incremental model. Both models work in cyclic (recurrent) fashion. Eq. 1 shows the classic model of definition [4] where the new weight of each factor c_j ($c_j \in$

n-factor FCM) at cycle (k+1) is defined from squashing the total effect of all factors ($c_1 \ldots c_n$ ∊ n-factor FCM) on c_j into a standard range of (0, 1) using a logistic function symmetrically around 0.5 (sigmoid curve).

$$c_j^{(k+1)} = \left(1 + e^{-\sum_{i=1}^{n} c_i^{(k)} e_{i,j}}\right)^{-1} \quad \text{, and} \quad j \in \{1 \ldots n\} \tag{1}$$

The total amount of the effect is in fact a sum of multiplications of each factor's weight (c_i) from the preceding cycle (k) by the weight of the respective causal link (effect $e_{i,j}$) which connects c_i to c_j. Through this process the factors' weights keep changing until state of convergence in which all factors (more importantly decision factors) converge to their finalized values (e.g., with convergence precision of ε= 0.001). The finalized weights are then used to interpret FCM's decision outputs. FCM can also support group decision making by aggregating multiple decision makers' views on a specific decision problem [11]. The model of [11] is regarded as a practical approach to group decision making using FCM-based inference mechanism. As depicted in Fig. 1, a group of individuals (here S students) can develop S independent FCMs (FCM_1 to FCM_s) by which they define the entire problem domain in their own way. The problem domain includes 1) the problem factors (FCM nodes), and 2) the causal relationships among affecting and affected factors (FCM edges). Therefore, each of the developed FCMs may result into different decision outputs as they have been set-up by independent students.

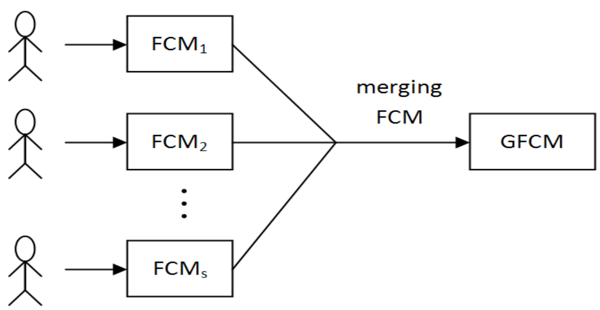

Fig. 1: Development of a group FCM [11]

To obtain consensus over decision outputs, an averaging strategy can be hired to define a group FCM (GFCM) from averaging all available FCMs. The averaging process for obtaining the weights of both factors' (c_j ∊ GFCM) and effects' ($e_{i,j}$ ∊ GFCM) involves summing all respective concepts and dividing them by S, as well as summing all respective effects and dividing them by S. Upon defining the GFCM, and running it for convergence, the ultimate decision outputs can be obtained. On the basis of the above idea, this paper presents an example of a 10-factor FCM where A … J are the factors which make up the FCM's graph, and $e_{A,A}$, $e_{A,B} \ldots e_{J,J}$ are 10^2 causal links (effects) among the 10 factors. There are 3 participants each required to set-up their own FCM by assigning random values to both factors and their effects. The resulted GFCM is the average of the 3 developed FCMs. Fig. 2 is presented to show the results on a student's FCM including defined initial weights of A … J, and the effect matrix {$e_{A,A}$, $e_{A,B}$, $e_{A,C}$ … $e_{A,I}$, $e_{A,J}$; $e_{B,A}$ … $e_{J,J}$} as given in Table 1. The finalized decision outputs are obtained upon running the FCM and reaching a convergence at 63rd cycle (with convergence precision of ε= 0.001).

Table 1: The applied effects matrix for the FCM of Fig. 2

	A	B	C	D	E	F	G	H	I	J
A	0.3674	0.4801	0.5787	-0.0310	-0.7754	-0.7805	0.3466	-0.8153	0	0.1115
B	-0.7358	-0.5303	-0.2647	-0.6963	0.5689	0.8675	-0.9409	-0.9844	0	-0.6311
C	0.4454	0.4699	-0.5879	0.5639	-0.4169	-0.6251	0.0965	-0.1538	0	-0.5759
D	0.7793	0.9412	-0.8267	0.7988	0.2071	-0.4676	0.2197	0.3111	0	-0.8453
E	-0.7650	0.7339	0.5439	-0.4119	0.9288	0.5957	-0.4103	0.4458	0	0.8276
F	0.2814	-0.8275	-0.5887	0.5253	-0.1350	-0.0248	0.3684	0.0624	0	0.4134
G	-0.3424	-0.2671	-0.2235	0.0617	0.3895	0.5379	0.5454	-0.7824	0	0.1156
H	0.3076	-0.2616	0.1036	0.8170	0.5162	-0.2080	0.4229	0.2635	0	-0.3731
I	0.4983	0.3701	-0.5421	-0.1894	-0.1347	-0.4541	0.7493	-0.7470	0	-0.6676
J	0.9664	0.1959	0.2839	0.6821	0.3110	-0.9255	0.7397	-0.7314	0	0.2450

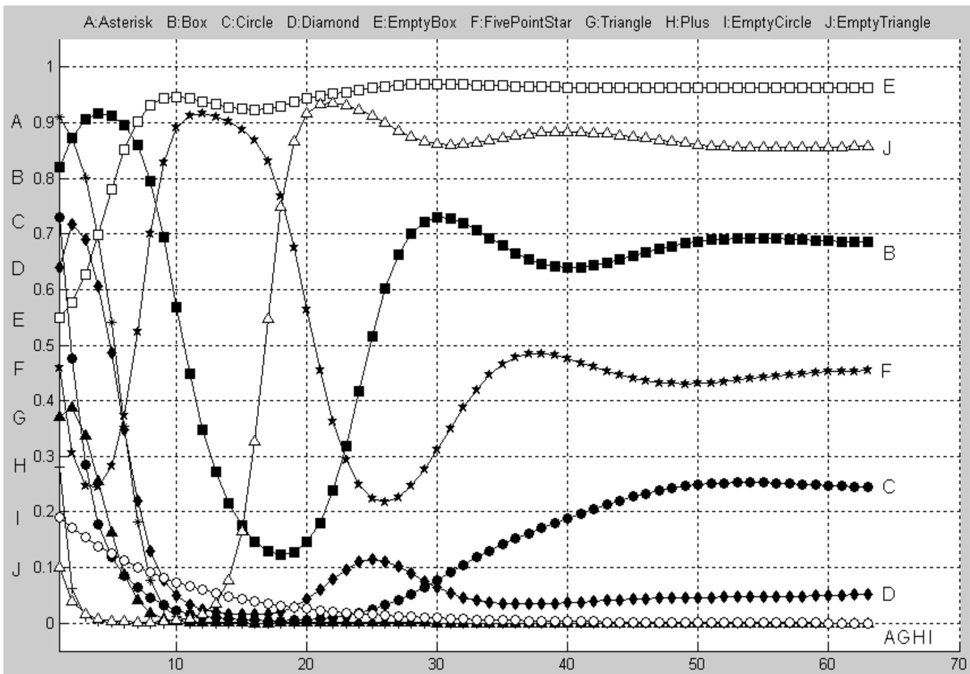

Fig. 2: The example GFCM model (with λ= 1, ε= 0.001). Initial weights of A … J have been: 0.91, 0.82, 0.73, 0.64, 0.55, 0.46, 0.37, 0.28, 0.19, 0.10. The example's effect matrix is given in Table 1.

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