Using ANFIS to Efficiently Model Skills and Beliefs in Computer-mediated Collaboration

Sofia J. Hadjileontiadou[1], Leontios J. Hadjileontiadis[2]

[1] Department of Civil Engineering
[2] Department of Electrical and Computer Engineering
Aristotle University, 54124 Thessaloniki, Greece
Email: sofiaal@civil.auth.gr leontios@auth.gr

Abstract. An approach in modeling collaborative and metacognitive data is presented in this paper. The proposed scheme, namely Collaboration/ Metacognition–Adaptive Network-based Fuzzy Inference System (C/M-ANFIS), uses neurofuzzy structure to adaptively infer on the relation between the above data in a meaningful way. More specifically, the collaborative and metacognitive data refer to the participant's collaborative *skills* and his/her *beliefs* on the quality of his/her collaboration respectively, during sessions of collaboration. The C/M-ANFIS allows the intense analysis of these empirical data facilitating a microgenetic look at how change in collaborative and metacognitive activity occurs *across* the sessions of collaboration. Moreover, through training procedures, the C/M-ANFIS model manages to estimate the processes that give rise to this change. Furthermore, based on the estimated relationship, the model may predict forthcoming values of a feedback indicator (quality of collaborative activity). This information, combined with coaching messages, may be presented to the users as an enhanced feedback.

1 Introduction

Artificial intelligence technologies play an important role in network collaboration, due to its advanced features and adaptive functionality. It contributes to proper support to the users by allowing adaptive modeling of their collaborative interactions in order to successfully track their individual skills and beliefs.

To this purpose, empirical data based models (EDM), which are mined from the large amount of data that are logged by the system during the computer-mediated interactions, may be used. The EDM rely on the fact that the intrinsic features of the observed interactions and their mutual interrelations can be learned from the data using a great number of simultaneously co-operating simple processing units or operations. This approach allows the extraction of information (knowledge) from these low-level data into other forms that might be more abstract [1]. Works in the area of EDM include the analysis of the quality of peers' interactions [2], and the modeling of the sequence of productive interactions [3].

When the analysis of interactions employs inference abilities to provide predictive utterances, the supporting system becomes even more enhanced. Examples include the use of a two-parameter regression model [4], and Bayesian networks [5]. Yet, system modeling based on conventional mathematical formulation, is not well suited for dealing with uncertain systems, such as human behavior. In contrast, EDM that make use of fuzzy inference system (FIS), utilizing fuzzy logic, combine numerical and linguistic data to model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis [6]. For enhanced performance, FIS could be combined with adaptive networks. The latter are network structures consisting of nodes and directional links through which the nodes are connected. Part or all of the nodes are adaptive; hence, each output of these nodes depends on the parameters pertaining to this node. The learning rule specifies how these parameters should be changed to minimize a prescribed error measure [7]. By embedding the FIS into the framework of adaptive networks, we obtain the neurofuzzy-model structure that adaptively maximizes the performance index through Adaptive Network-based FIS (ANFIS) [8].

In this paper, an adaptive neurofuzzy EDM, namely Collaboration/Metacognition–ANFIS (C/M-ANFIS) model is proposed, to efficiently model the collaborators' skills and beliefs. In particular, the C/M-ANFIS model combines ANFIS with sets of collaborative and metacognitive data, acquired with a suitable Internet-based collaboration tool [9,10], during peers' computer-mediated collaboration. The collaborative and metacognitive data refer to peers' collaborative activity and to their beliefs on the quality of their collaboration, respectively. Based on these data the C/M-ANFIS model manages, through training procedures, to extract the collaborative strategy adopted by the peers, independently of the task-content. When adequately trained, the model manages to generalize on each peer's collaborative behavior, thus provide predictions on his/her collaborative activity in a forthcoming collaborative session. Based on this modeling, individual support could be provided to each peer that could contribute to improve his/her collaboration management. Materialization of the C/M-ANFIS model based upon experimental data from the collaboration of distant pairs of students in environmental engineering education proves the feasibility of the proposed approach.

The remainder of this paper is organized as follows. In Section 2, information regarding the empirical data of interest is provided. In Section 3, the structure of the proposed C/M-ANFIS model is presented. Model development issues and results are presented and discussed in Sections 4 and 5 respectively. Finally, Section 6 concludes the work.

2 Empirical Data of Interest

The proposed EDM approach models information that is hidden in the peers' interactions during computer mediated collaboration. In the following subsections the type of these empirical data and their acquisition procedure are described.

2.1 Types of data

The activity that takes place during the collaboration involves a variety of interactions. This work focuses on data that result from collaborative and metacognitive interactions, briefly described as follows.

During collaboration two or more people, sharing the same objective, are engaged in a common activity in order to transform the objective to an outcome. In order this transformation to be achieved, the construction and maintenance of effective collaborative activities is fundamental [11]. To do so, in a computer-mediated environment, a communication model is established, to challenge certain types of interactions that are expected to promote a more effective collaborative activity. Such collaborative interactions include creative conflict, productive argumentation, knowledge sharing, and critique provision [11] and are differentiated through button clicks on predefined areas of the interfaces. The system logs this activity and these raw data are further elaborated by means of *intermediate collaborative variables* that can be empirically and theoretically related to the conditions of collaboration and to the particular outcome [11]. In this way, a new series of data are produced, namely collaborative data.

Metacognition includes individual's awareness of his/her own knowledge, actions, and emotional situation, along with the ability to monitor and consciously adjust them during a learning procedure (e.g. collaboration) [12, 13]. The use of metacognition may significantly improve the individual's collaborative performance [14]. Hence, adopting metacognitive strategies upon a collaborative procedure the individual is able to consciously monitor his/her collaborative interactions and adjust them in order to enhance the effectiveness of his/her collaborative activity. The metacognitive activity is conscious and countable [15], therefore it is translatable through metacognitive interactions. These interactions are also captured by means of a communication model and properly designed interfaces. Such metacognitive interactions include explaining/self-explaining one's own thinking and describing planned actions according to the individual's beliefs. Similarly to the collaborative interactions, *intermediate metacognitive variables,* which can be used in the quantitative interpretation of metacognitive interactions, could be defined, leading to a series of elaborated data, namely metacognitive data.

As it has been made clear from the analysis so far, the aim of this work is to model cognitive and metacognitive interactions using data derived from the peer's collaboration monitoring, focusing on his/her collaborative activity, rather than on his/her performance at the task level. In the proposed work, these data are acquired through a collaboration environment, namely Lin2k [9, 10], which monitors the peer's collaboration activity. By employing a FIS the Lin2k elaborates the peer's collaboration and metacognition activity providing the appropriate collaborative and metacognitive input/output data for the proposed C/M-ANFIS model. A brief description of the Lin2k follows.

2.2 Data Acquisition

Lin2k is a computer-mediated environment that supports the collaboration between two distant peers in an asynchronous written mode [9, 10]. The collaboration is developed in a step-by-step approach of a case study, and the peers communicate through the Internet using semi-structured interfaces [9]. These interfaces facilitate the peers in performing the collaborative interactions. By the end of each step, each peer is challenged to perform reflection on his/her preceded collaborative activity and to plan the improvement of his/her collaborative activity during the next step. Again by means of interfaces dedicated to this purpose, each peer performs these metacognitive interactions. Both collaborative and metacognitive interactions are logged by the system as raw empirical data at each step. During the collaborative/metacognitive activity, intermediate collaborative and metacognitive variables are fired. These intermediate variables are quantified by the system through weighting of the raw data and are archived in a peer's activity database. The acquired values of the intermediate collaborative variables are used for the estimation of the *quality of the collaborative activity*. The term quality refers to the domain-expert's knowledge of 'proper' collaboration [9, 10]. Similarly, the acquired values of the intermediate metacognitive variables are used for the estimation of the peer's *intention of improvement* during the collaborative activity [9, 10]. The intention of improvement reflects the user's metacognitive awareness of the quality of his/her collaborative-activity and beliefs for further improvement [9, 16]. The Lin2k employs FIS, i.e., Collaboration/ Metacognition-FIS (C/M-FIS), to provide a quantitative estimation of the collaboration quality and the intention of improvement. Using appropriate IF-THEN fuzzy rules and membership functions based on expert's knowledge [9,10], the Lin2k combines the acquired values of the intermediate variables to infer two crisp values at each step of the case study, i.e., $C_n^s(p)$ and $M_n^s(p)$, where $n = A, B$ denotes the student, $p = 1,\ldots,N$ the pair, and $s = 1,\ldots L$ the step of the case study. The $C_n^s(p)$ and $M_n^s(p)$ values are used as measures of the collaboration quality and the intention of improvement, respectively. The collaborative and metacognitive data, $C_n^s(p)$ and $M_n^s(p)$ respectively, define the input signal of the proposed C/M-ANFIS model.

3 The Structure of the Proposed Model

The C/M-ANFIS model is expected to estimate the peer's collaborative activity of the next step $\widetilde{C}_n^{s+1}(p)$, prior to the concrete collaborative experience, when presented with current $C_n^s(p)$ and $M_n^s(p)$ values. To infer the $\widetilde{C}_n^{s+1}(p)$ value, the C/M-ANFIS model is trained to evaluate the relation between the forthcoming collaborative activity with the current collaborative and metacognitive activity. However, this initially unknown relation is hidden within the empirical data that are obtained from the Lin2k. Therefore, C/M-ANFIS training is an equivalent procedure to learning from empirical data. This coincides with ANFIS structure [7] and motivated its use in the present study. In fact, C/M-ANFIS is based on an ANFIS five-layer feed-forward network structure, as depicted in Figure 1. During training, at each level, the parameterized nodes perform specific functions of the incoming signal, as follows.

Suppose for simplicity, that the C/M-ANFIS rule-base contains two rules of Sugeno type [8]:

R1: IF $C_n^s(p)$ is A_1 AND $M_n^s(p)$ is B_1 THEN $f_1 = p_1 C_n^s(p) + q_1 M_n^s(p) + r_1$ ELSE,

R2: IF $C_n^s(p)$ is A_2 OR $M_n^s(p)$ is B_2 THEN $f_2 = p_2 C_n^s(p) + q_2 M_n^s(p) + r_2$,

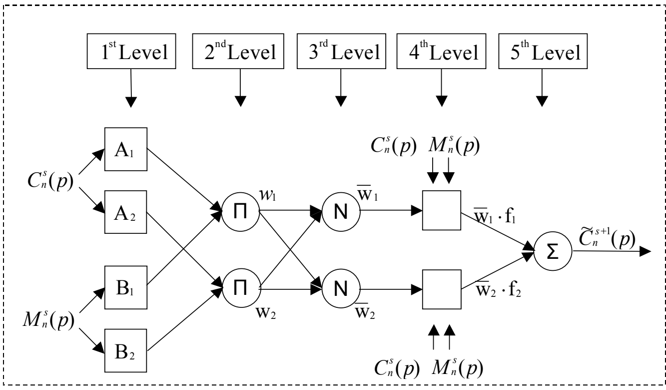

Fig. 1. The use of the ANFIS architecture [7] in the C/M-ANFIS model structure. The graph refers to the *s* step of the collaborative case study

where A_i, B_i and p_i, q_i, r_i, with $i = 1, 2$, are linguistic variables and constants, respectively [8]. The ith node function of the first layer performs fuzzyfication of the incoming signal as follows (see also Figure 1):

$$O_{C_i}{}^1 = \mu_{A_i}(C_n^s(p)), O_{M_i}{}^1 = \mu_{B_i}(M_n^s(p)), i = 1,2, \qquad \textbf{(1)}$$

where μ_{A_i}, μ_{B_i} denote the membership functions that specify the degree to which $C_n^s(p)$ and $M_n^s(p)$ belong to the corresponding linguistic variables A_i and B_i, respectively. $O_{C_i}^1$ and $O_{M_i}^1$ describe the collaborative and metacognitive activity, respectively, using fuzzy values (i.e., low or good collaboration; low or satisfactory metacognition). The shape of the continuous and piecewise differentiable membership functions is described by parameters. These are the premise parameters and are adjusted by using the learning algorithm. Each node of the second layer O_i^2 presents the firing strength of a rule, estimated by multiplying the incoming membership values of the previous layer:

$$O_i^2 = w_i = O_{Ci}^1 \cdot O_{Mi}^1, \ i = 1,2 . \qquad \textbf{(2)}$$

The ith node of the third layer O_i^3 normalizes the firing strength of the rules:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2. \qquad \textbf{(3)}$$

The node function at the fourth level is of the form:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i C_n^s(p) + q_i M_n^s(p) + r_i), \ i = 1,2, \qquad \textbf{(4)}$$

where $\{p_i, q_i, r_i\}$ are the consequent parameters. A single node constitutes the fifth layer, which computes the overall crisp output:

$$O_i^5 = \widetilde{C}_n^{s+1}(p) = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \,. \qquad \textbf{(5)}$$

The overall development of the C/M-ANFIS model requires the following primary procedures:

1. Data acquisition. The Lin2k collaborative environment provides the data of interest. Let the following vectors:

$$\mathbf{Z}_C^{1:L}(p) = [C_A^1(p), C_A^2(p), \ldots, C_A^L(p), C_B^1(p), C_B^2(p), \ldots, C_B^L(p)]^T \,, \qquad \textbf{(6)}$$

$$\mathbf{Z}_M^{1:L}(p) = [M_A^1(p), M_A^2(p), \ldots, M_A^L(p), M_B^1(p), M_B^2(p), \ldots, M_B^L(p)]^T \,. \qquad \textbf{(7)}$$

The input/output pairs

$$\mathbf{y} = \begin{bmatrix} Z_C^{1:L-1}(1) & Z_M^{1:L-1}(1) \\ Z_C^{1:L-1}(2) & Z_M^{1:L-1}(2) \\ \vdots & \vdots \\ Z_C^{1:L-1}(N) & Z_M^{1:L-1}(N) \end{bmatrix}, \qquad \textbf{(8)}$$

$$\mathbf{w} = [Z_C^{2:L}(1), Z_C^{2:L}(2), \ldots, Z_C^{2:L}(N)]^T \,, \qquad \textbf{(9)}$$

are defined respectively.

2. Definition of the Training and Testing Data Set. From the overall input/output data, 75% are normally used for the training procedure, while the rest 25% for model testing, as described below.
3. Training procedure. The input/output pairs are all presented to the system during the C/M-ANFIS model training. Learning is implemented in epochs in order to define the values of the premise and consequent parameters by minimizing, with a predefined accuracy, the Root Mean-Squared Error ($RMSE$),

$$RMSE = \sqrt{\frac{(\mathbf{w} - \widetilde{\mathbf{w}})^T (\mathbf{w} - \widetilde{\mathbf{w}})}{2(L-1)N - 1}} \,, \qquad \textbf{(10)}$$

where $\widetilde{\mathbf{w}}$ denotes the estimated value of $\mathbf{w}$. Each epoch foresees two passes: a forward pass of the signal, where the premise parameters are kept fixed and the consequent parameters are calculated by the least squares method, and a backward pass, where the consequent parameters are kept fixed and the premise parameters are updated by the gradient descent method [7, 8].

4. Testing procedure. The testing data set is presented to the model and the equivalent *RMSE* is calculated. When this value is within a predefined accuracy, the generalization ability of the model is verified. Such generalization equals to prediction of the quality of the peer's collaborative activity in a forthcoming collaborative session, which may ground the provision of advanced individualized feedback, towards self-improvement.

4 Development of the Proposed Model

An experimental use of Lin2k provided the empirical data for the development of the C/M-ANFIS model. The overall data set was obtained from the distant collaboration of 44 pairs of civil engineering students (7^{th} semester) at the Department of Civil Engineering, Aristotle University of Thessaloniki, Greece. They were randomly selected, and they collaborated on two case studies, which were set in the course of environmental technology concerning everyday problems. The aim of the peers' collaboration was to incrementally produce a written technical report on those problems, at six successive steps of collaboration. In this way, the two-input one-output training vectors that were obtained were the ones described by (8) and (9), respectively, with L=6 and N=44. The overall empirical data were 88 input-output vectors. In order not only to train but also to test the training of the C/M-ANFIS model, 75% of the empirical data was used for the training procedure while the rest 25% for model testing.

During the C/M-ANFIS training, the training set up foresaw the analytical forms of prod and probor operators for the connectors AND and OR, respectively, the min for the IF-THEN implication and the max for the ELSE aggregation (see linguistic terms in the aforementioned rules R1 and R2), and the defuzzification method wtaver produced the crisp output [17]. The whole procedure was implemented on a Pentium III 650 MHz, using Matlab 5.3 (Mathworks Inc., Natick, MA) [18].

	Input Variable $C_n^s(p)$				Input Variable $M_n^s(p)$			
	$sig1$	$c1$	$sig2$	$c2$	$sig1$	$c1$	$sig2$	$c2$
1	0.01887	0.03333	0.02244	0.03483	0.01887	0.03333	0.01887	0.03333
2	0.01772	0.07832	0.01619	0.14240	0.01887	0.07778	0.01887	0.14440
3	0.02236	0.18670	0.01891	0.25560	0.01887	0.18890	0.02024	0.25600
4	0.02228	0.29890	0.01672	0.36600	0.01887	0.30000	0.01651	0.36490
5	0.01824	0.41160	0.01863	0.47760	0.01824	0.41050	0.01977	0.47820
6	0.01893	0.52220	0.01887	0.58890	0.01899	0.52230	0.01899	0.59030
7	0.01887	0.63330	0.01887	0.70000	0.01606	0.63580	0.01862	0.69950
8	0.01887	0.74440	0.01887	0.81110	0.02131	0.74290	0.02333	0.81290
9	0.01887	0.85560	0.01887	0.92220	0.01885	0.85560	0.01887	0.92220
10	0.01887	0.96670	0.01887	1.03300	0.02278	0.96470	0.01887	1.03300

Table 1. Vectors that define the membership functions of the best-trained version of the C/M-ANFIS model

The C/M-ANFIS model training aimed at selecting the premise and consequent parameters by minimizing, with an accuracy of 0.01, the *RMSE*. Different set up [18] were tested during the training procedure, resulting in the best-trained version of the C/M-ANFIS model within 3 epochs. This version resulted in Training *RMSEs* 0.11436, Testing *RMSEs* 0.088495 and ten membership functions assigned to each input variable, $C_n^s(p)$ and $M_n^s(p)$, respectively. The shape of each membership function is of the Gauss2mf (Gaussian combination) type and is defined by a vector of four parameters listed in the order of $[sig1, c1, sig2, c2]$ (where combinations of

sig and c, determine the shape of the left-most and right-most curve, respectively [17]). The vectors, which define the membership functions, are presented in Table 1.

Moreover, 100 rules resulted in the best-trained version of the C/M-ANFIS model. This quite high number of rules is due to its effort to model the unknown relation between $C_n^s(p)$ and $M_n^s(p)$ data.

5 Discussion

This work presents the use neurofuzzy modeling to generalize from empirical data and reveal the rules that govern the outcome of peers' collaborative and metacognitive activities, during computer-mediated collaboration. In particular the proposed approach contributes to modeling the correlation of the peer's cognitive and metacognitive activity or otherwise the peer's *skills* and *beliefs* during a collaborative activity, introducing another level of abstraction for the realization and interpretation of hidden and complex relations in human interactions.

Based on this knowledge, efficient and individual support could be provided to each collaborator. More specifically, the adaptive character of the C/M-ANFIS model by inferring on collaborative and metacognitive data foresees the status of collaboration in the next step (estimated $\widetilde{C}_n^{s+1}(p)$ value) and thus, may ground early support to the peers to improve their collaborative activity in the forthcoming step of collaboration.

The above approach materializes a noteworthy characteristic of the C/M-ANFIS model i.e., its microgenetic design [19], which calls for a closer look at how change in behavior occurs as individuals go through a learning experience [20]. In particular, the C/M-ANFIS model observes the *changes* of the individual collaborative behavior *during* a period of time. Moreover, the observed behaviors are *intensively analyzed* [19], through the neurofuzzy methodology with the goal of identifying the processes that give rise to the change.

The C/M-ANFIS model, through the aforementioned microgenetic design, elicits from empirical observations and makes explicit the behavioral patterns of change of the peer's cognitive and metacognitive activity, *during* incremented sessions of collaboration. However, the approach to observe and realize behavioral change calls for not only a meticulous observation of how the change occurs, but also the possibility of an impetus for change [21]. A planned change at the micro-level of interactions may give rise to new patterns of the collaborative behavior at the macro-level [20], i.e., to provoke overall collaborative skills improvement. The C/M-ANFIS model contributes to the occurrence and acceleration of this change by providing new meaningful information at the micro-level [20]. More specifically, by presenting to the individual, at successive intervals of the micro-level (end of each step of the case study), the estimated value of the forthcoming collaborative activity $\widetilde{C}_n^{s+1}(p)$, it highly increases the possibilities to cause the desired change. Consequently, the C/M-ANFIS may contribute to a formatively improvement of the peer's collaborative behavior.

6 Conclusions and Future Work

A new approach in modeling empirical data during computer-mediated collaboration is presented in this paper. The proposed C/M-ANFIS model, when embedded in an Internet-based collaborative environment, such as Lin2k, uses neurofuzzy structure to adaptively infer on the relation between skills (collaborative data) and beliefs (metacognitive data) of the collaborator, as far as his/her collaborative performance is concerned. Moreover, it manages to generalize on this relation and provide estimations of his/her collaborative performance in a forthcoming session of collaboration. This information may provoke creative changes in the micro- and macro-level of peers' collaborative activity, thus significantly contributing to the enhancement of the provided support. Training and testing results from the materialization of the C/M-ANFIS model, using empirical collaborative data from the environmental education field, prove its fast convergence to minimum error, its ability to accurately generalize from data, and its predictive performance.

Like all EDM, the C/M-ANFIS needs sufficient amount of data in order to enhance its performance, i.e., to increase its generalization ability with simultaneous minimization of its training error, which constitutes the direction of future work. Nevertheless, its low computational complexity, its modular character, and its task-content independence, enables it to be easily integrated into other collaboration environments, similar to Lin2k, applied in a variety of collaborative case studies.

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