Chapter 11

ANFIS–Based Collaborative/Metacognitive Data Modeling

ABSTRACT

Stemming from the approach presented in the previous chapter, this chapter extends the previous modeling concept further, by adopting Adaptive Neuro-Fuzzy Inference System (ANFIS) as the engine to model the collaborative and metacognitive data that are logged during peers’ computer-mediated collaboration. The realization of this approach, namely collaboration/metacognition ANFIS (C/M-ANFIS), along with experimental uses and extensions of it, are described in detail. From an overall perspective, the C/M-ANFIS provides innovative opportunities for teaching and learning, on the basis of embedding the fuzzy logic concept within the educational practice, as it equips them with dynamic collaborative performance forecasting capabilities. This reinforces the transitional change of the peers’ collaborative and metacognitive skills, gravitating them towards higher quality and more balanced computer-mediated collaboration.

INTRODUCTION

In the previous chapter (chapter 10), an a priori knowledge-based model, namely collaboration/metacognition-fuzzy inference system (C/M-FIS), was presented, which employed FIS (see chapter 8) to model the collaborative and metacognitive activity of peers during their collaboration within a computer-supported collaborative learning (CSCL) environment. In this chapter, an extension to this perspective is followed, in an effort to approach the same modeling problem, yet from a different angle. In particular, the scope is to use empirical data-based models (EDMs), which are mined from the large amount of data that are logged by the system during the computer-mediated interactions and are a priori knowledge-free. 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 (Fayyad et al., 1996; Chen et al., 2011).

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EDMs have been mainly used for revealing characteristics hidden in data. Works in this area include the analysis of the quality of peers' interactions (Soller & Lesgold, 2000a), and the modeling of the sequence of productive interactions (Soller & Lesgold, 2000b). When the interactions analysis employs inference abilities to provide predictive utterances, the supporting system becomes even more enhanced. An example is given in (Beck et al., 1997), where a two parameter regression model predicts how a student will perform in the future, based on a student model that is developed within a statistical framework. In addition, Bayesian networks (BNs) (Derry & DuRussel, 1999) have been used to represent causal relations in peers’ behavior (Reye, 1996), modeling pedagogical decisions (Gerner et al., 1998), modeling the learner’s level of understanding in collaborative learning (Komedani et al., 2005), and determination of peer’s level of competence within a domain (Collins et al., 1996). Although BNs have been shown to be highly effective in modeling the user’s behavior, they exhibit some difficulties in implementation, in determining how evidence propagates, and in estimating the edge probabilities (Beck & Stern, 1999).

EDM that make use of a FIS combine numerical and linguistic data to model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis (Beck & Stern, 1999). For enhanced performance, FIS could be combined with adaptive networks. As presented in chapter 8, 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 (Jang, 1992). By embedding the FIS into the framework of adaptive networks, we obtain the neuro-fuzzy model structure that adaptively maximizes the performance index through Adaptive Network-based FIS (ANFIS) (Jang, 1993; chapter 8).

Motivated by the aforementioned concept, this chapter presents an adaptive neuro-fuzzy EDM, namely Collaboration/Metacognition–ANFIS (C/M-ANFIS) model, which combines ANFIS with sets of collaborative and metacognitive data, the same as those described in chapter 10, and acquired with the same CSCL tool, i.e., the Lin2k (Hadjileontiadou et al., 2003), during peers’ computer-mediated collaboration. The acquired data refer to peers’ collaborative activity and to their beliefs on the quality of their collaboration, respectively; hence, when these data are utilized by neuro-fuzzy structures in the C/M-ANFIS, the advantages described in the case of C/M-FIS (consideration of both collaborative and metacognitive activities, adaptation of the feedback presented to each peer to his/her collaborative skill, and focus on the user’s behavior despite the particular task-content) are enriched with the following two:

- By extracting the common collaborative strategy adopted by each peer we can generalize his/her collaborative behavior, and
- The peer’s collaboration activity in a forthcoming collaborative session can be potentially predicted.

It is worthy to note that the provision of feedback to the user is focused on his/her collaborative activity, rather than on his/her performance at the task level, using data derived from his/her collaboration monitoring. The latter could be derived from a variety of computer-supported collaborative environments, involving Web-based pages and/or micro/macro-scripts, with the latter often used in mobile (m-) learning (Dillenbourg & Crivelli, 2011).

The above characteristics define a new approach in modeling peers’ collaborative activity. Based on this modeling, individual support could be provided to each peer that could contribute to improve his/her collaboration management. A graphical representation of the proposed process is shown in Figure 1.