Student modeling using fuzzy logic and neural networks

Regina Stathacopoulou[1]

Department of Informatics and Telecommunications, University of Athens, Panepistimiopolis, GR-15784 Athens, Greece
sreg@di.uoa.gr

Abstract. In this thesis a neural network-based fuzzy modeling approach to assess student learning characteristic and update the student model in Intelligent Learning Environments is proposed. The neural network-based fuzzy diagnostic model is a general diagnostic model which can be used to implement the diagnostic process in any learning environment according to designers' and teachers' suggestions. Fuzzy logic is used to provide a linguistic description of students' behavior and learning characteristics, as they have been elicited from teachers, and to handle the inherent uncertainty associated with teachers' subjective assessments. Neural networks are used to add learning and generalization abilities to the fuzzy model by encoding teachers' experience through supervised neural-network learning. The model has been successfully implemented, trained and tested in the learning environment "Vectors in Physics and Mathematics" by using the recommendations of a group of five experienced teachers.

1 Introduction

Student models are distinguishing features of both Intelligent Tutoring Systems (ITS) [16] [17] and Intelligent Learning Environments (ILE) [1]. Ideally, a student model should include all aspects of students' behavior and knowledge which have repercussions on their performance and learning [17]. In practice, the contents of a student model depend on the application. It normally includes learner goals and plans, capabilities, attitudes and/or knowledge or beliefs, and is used as a tool for adapting ILE behavior to the individual student [16]. Inferring a student model is called diagnosis, because it is much like the medical task of inferring a hidden physiological state from observable signs [16], i.e. the ILE uncovers a hidden cognitive state (student characteristics) from observable behavior.

The term *student behavior* can be used to refer to a student's observable response to a particular stimulus in a given domain which, together with the stimulus, serves as the primary input to the student modeling system [13]. The input can be an action or the result of that action, and can also include intermediate results [13]. From this input, the diagnosis unit must infer a student's unobservable behavior [16]. Clearly,

1 Supervisor: Maria Grigoriadou, Associate Professor

the less information the unit has the harder its task is [16]. This makes student modeling a difficult process, given that the evidence about a student's behavior provided by the student's inputs to an ILE is usually scanty [16], and contains a good deal of uncertainty [7]. A variety of AI techniques have been proposed for this purpose.

Bayesian networks have been proposed in ANDES [2], in order to relate — in a probabilistic way — a student's observable behavior to a particular piece of his/her knowledge. Unsupervized machine learning techniques have also been proposed [13], in order to discover classes of errors, which represent misconceptions and other knowledge errors, from discrepancies in students' behavior.

Another approach to handle the inherent uncertainty in a student's behavior and to achieve a human description of knowledge is to use fuzzy logic. One of the first attempts in using fuzzy student modeling, which was revised some years later [6], has been proposed in TAPS by Hawkes *et al*. In this context, fuzzy logic has been proposed as a flexible and realistic method of easily capturing the way human tutors might evaluate a student and handle tutoring decisions which are not clear-cut. Towards this direction, several other attempts have been proposed in the literature to model student knowledge, mental states and progress as well as student cognitive abilities and personal characteristics. A comprehensive review can be found in [7].

Neural networks have also been proposed in student modeling due to their abilities to learn from noisy or incomplete patterns of students' behavior and generalize over similar examples [12]. This generalized knowledge can then be used to recognize unknown sequences. A problem which arises when trying to apply a neural network to modeling human behavior is knowledge representation. The black-box characteristics of neural networks cannot offer much help, since the weights learned are often difficult for humans to interpret. To alleviate this situation, a neural network approach in which each node and connection has symbolic meaning has been proposed in TAPS [12]. The back-propagation algorithm has been used to modify weights which represent importance measures of attributes associated with student performance, in order to refine and expand incomplete expert knowledge.

Along these lines, this thesis presents a neuro-fuzzy synergism for student diagnosis, by using teachers' expertise in implementing a neural-network based fuzzy diagnostic model in assessing students' learning characteristics and update the student model. The neural network-based fuzzy diagnostic model [14] is a general diagnostic model which can be used to implement the diagnostic process in any learning environment according to designers' and teachers' suggestions. Fuzzy logic is used to provide a linguistic description of students' behavior and learning characteristics, as they have been elicited from teachers, and to handle the inherent uncertainty associated with teachers' subjective assessments. In addition, through the mode of qualitative reasoning teachers' knowledge is represented in a way that can be interpreted by designers of Intelligent Learning Environments. Neural networks are used to add learning and generalization abilities to the fuzzy model, in case where teachers' reasoning is not well defined and available in the form of fuzzy if-then rules, in order to encode teachers' intuitive assessments — available by means of examples — into the system. The neural network-based fuzzy diagnostic model has been tested in evaluating students' learning characteristics, in the learning environment "Vectors in Physics and Mathematics" using the recommendations of a group of five experts teachers.

2 The neural network-based fuzzy diagnostic model

Depending on the type of learning environment, domain and instructional design, teachers provide the learning characteristics they use to discriminate among students for the purpose of adapting their educational strategies to students' individual differences. Teachers may provide several student characteristics [4] related to student knowledge, learning abilities, motivation, learning strategies and learning styles. The output of the neural network-based fuzzy diagnostic model updates the student model regarding *L* different learning characteristics C_1, C_2,..., C_L, such as aspects of a student's learning style, learning abilities and motivation.

Depending on the learning characteristic teachers provide the types of evidences they use to discriminate among students [4]. Teachers may provide several types of evidences B_1, B_2,…, B_i,…, B_k such as, students' not random mouse moves, number of students' conceptual errors, total time spent on task, number of idle intervals etc. The set of names of the types of evidences B={B_1, B_2,…, B_i,…, B_k} describes linguistically the *k* aspects of a student's observable behavior which will be used to evaluate a student's learning characteristic. From a student's actions related to each type of evidence B_i (i=1,2,…,k), a measured numeric value x_i (i=1,2,…,k), where $x_i \in U_i$, U_i (i=1,2,…,k), $U_i \subset \Re^+$ (for example, total time working on the scenario, number of idle intervals) is calculated for a student, in order to define the numeric input X= {x_1,…,x_i,…,x_k} to the neural network-based fuzzy diagnostic model which corresponds to a student's observable behavior B={B_1, B_2,…, B_i,…, B_k}.

In the fuzzy model the numeric input X= {x_1,…,x_i,…,x_k} is fuzzified and processed through a set of fuzzy systems, with an approach which is closer to the human decision making process, since decisions are made by combining fuzzy evidences, each one contributing to the final decision to some degree. The fuzzy model is implemented with a set of neural networks. A student's evaluation regarding each learning characteristic, C_1,…, C_j,…, C_L is assessed by processing the numerical input X= {x_1,…,x_i,…, x_k}, of a student's behavior through a set of neural networks. The process consists of three stages: fuzzification, inference, and defuzzification (Figure 1).

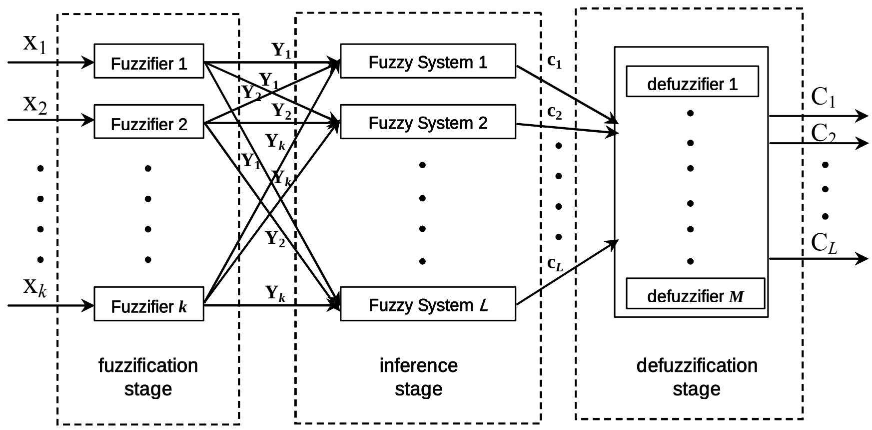

Fig. 1. Schematic of the diagnostic model

2.1 Fuzzy Knowledge Representation Scheme

Fuzzification stage (stage 1): This stage represents teachers' subjective linguistic description of a student's behavior B={B_1, B_2,…, B_i,…, B_k}(e.g. s/he draws a vector after a *long* time, s/he has answered *enough* questions in the pre-test). We use linguistic variables [18] to describe the types of evidence B_1,…, B_i,…, B_k, of student behavior B. The expert-teachers set the number f_i of the linguistic values of each linguistic variable B_i (i=1,2,…,k) and their names $V_{i1}, V_{i2}, \ldots, V_{if_i}$, according to their personal judgement. The set T(B_i)= { $V_{i1}, V_{i2}, \ldots, V_{if_i}$ } is the term set of B_i(i=1, 2,…, k). For example, the corresponding term set of the linguistic variable B_i = "*total time on the scenario*" could be T(B_i) = { V_{i1}, V_{i2}, V_{i3} }={*Short*, *Normal*, *Long*} or T(B_i)= { $V_{i1}, V_{i2}, V_{i3}, V_{i4}, V_{i5}$ } = {*Very Short*, *Short*, *Normal*, *Long*, *Very Long*} including three (f_i=3), or five (f_i=5) linguistic values respectively. At the fuzzification stage, each element x_i (i=1,2,…,k) $x_i \in U_i$, U_i (i=1,2,…,k), $U_i \subset \Re^+$ of the numeric input $X = \{x_1, x_2, ..., x_k\}$, is transformed into numeric values y_{if_i} in [0,1] which represent membership degrees Y_i=($y_{i1}, y_{i2}, \ldots, y_{if_i}$) (i=1,2,…,k) to the linguistic values $V_{i1}, V_{i2}, \ldots, V_{if_i}$ which describe a type of evidence B_i (i=1,2,…,k).

Inference Stage (stage 2): This stage represents teachers' reasoning in categorizing students qualitatively according to their learning characteristics, such as *attentive*, *rather slow*, *good*, etc. In particular, an approximation of fuzzy IF-THEN rules is performed, which represent teachers' reasoning in the qualitative assessment of students' characteristics. For example, *if a student's the total time on the scenario is large and the number of attempts to find the correct forces is large and the number of random mouse moves is small, then the student is very interested in the scenario*. We use linguistic variables [18] to describe a student's characteristics C_1,…, C_j,…, C_L. The expert-teachers set the number m_j of the linguistic values and their names $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ for each characteristic C_j (j=1, 2,…, L) according to their personal judgement. The set T(C_j)={ $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ } is the term set of C_j (j=1,2,…,L). For example, the term set of the linguistic variable C_j = "*student interest*" could be: T(C_j) = { $C_{j1}, C_{j2}, C_{j3}, C_{j4}, C_{j5}$ } = {*very bored*, *bored*, *neither interested neither bored*, *interested*, *very interested*} using five linguistic values (m_j =5). In this way, a mode of qualitative reasoning, in which the preconditions and the consequents involve fuzzy variables [18], is used to provide an imprecise description of teachers' reasoning:

$$\text{" IF } B_1 \text{ is } V_{1I_1} \text{ AND } B_2 \text{ is } V_{2I_2} \ldots \text{AND } B_k \text{ is } V_{kI_k} \quad \text{THEN} \quad C_1 \text{ is } C_{1J_1} \text{ AND } C_2 \text{ is } C_{2J_2} \ldots \text{AND } C_L \text{ is } C_{LJ_L} \text{"}$$

where I_1=1,2,…,f_1; I_2=1,2,…,f_2; I_k=1,2,…,f_k; J_1=1,2,…, m_1; J_2=1,2,…,m_2; J_L=1,2,…,m_L.

The inference stage, provides a fuzzy assessment c_j= [$c_{j1}, c_{j2}, \ldots, c_{jm_j}$], (j=1, 2,…, L) of a student's characteristics, C_1, C_2, …, C_L, by assessing membership degrees $c_{j1}, c_{j2}, \ldots, c_{jm_j}$ to the linguistic values $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ of the linguistic variable C_j (j=1, 2,…, L) that describe the characteristic C_j (j=1, 2,…, L). We use fuzzy relations [11], operated with the *max-min* composition operator in order to infer a fuzzy assessment c_j= [$c_{j1}, c_{j2}, \ldots, c_{jm_j}$], (j=1, 2,…, L) from a fuzzy precondition.

Defuzzification Stage (stage 3): This stage represents teachers' final decision in classifying a student in one of the predefined linguistic values $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ of the characteristic C_j (j=1, 2,…, L). The fuzzy assessments c_j= [$c_{j1}, c_{j2}, \ldots, c_{jm_j}$] (j=1, 2, …,L) are defuzzified to non-fuzzy values, that is to say, to decisions on one of the linguistic values $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ (j=1,2,…,L) of the learning characteristic C_j (j=1,2,…,L).

2.2 Neural network implementation of the fuzzy model

Fuzzification stage (stage 1): In the first stage the numeric input $X = \{x_1, ..., x_i, ..., x_k\}$, is fuzzified with a set of k fuzzifiers. The i–th fuzzifier (i=1,2,…,k) transforms the numeric input x_i into membership degrees Y_i = ($y_{i1}, y_{i2}, \ldots, y_{if_i}$), (i=1,2,…,k) of the linguistic values $V_{i1}, V_{i2}, \ldots, V_{if_i}$ which describe each type of evidence B_i (i=1,2,…,k). The fuzzifier stage is implemented with a set of k fixed weight neural networks which calculate the membership functions $y_{i1}(x_i), y_{i2}(x_i), \ldots, y_{if_i}(x_i) \quad x_\iota \in U_\iota$ of the linguistic values $V_{i1}, V_{i2}, \ldots, V_{if_i}$ using a library of regular shapes [8]. We have used sigmoid functions as membership functions $y_{i1}(x_i)$ and $y_{if_i}(x_i) \quad x_\iota \in U_\iota$ for the extreme linguistic values V_{i1} and V_{if_i}, and pseudotrapezoidal functions as membership functions $y_{i2}(x_i), \ldots, y_{if_i - 1}(x_i)$ for the intermediate values $V_{i2}, \ldots, V_{if_i - 1}$. Since membership functions are subjective and generally context-dependent, i.e. teacher —and subject matter— dependent, [18], a set $M = \{m_1, m_2, ..., m_i, ..., m_k\}$ of parameters which adjust the membership functions [14] to teachers' subjective linguistic description is defined.

Inference Stage (stage 2): In the second stage, a set of L fuzzy systems is used to provide a fuzzy assessment c_1, c_2,…, c_j,…, c_L, of a student's learning characteristics C_1, C_2,…, C_j,…, C_L. Each system j, (j=1, 2,…, L) infers about a particular learning characteristic C_j (j=1,2,…,L) . by assessing membership degrees $c_{j1}, c_{j2}, \ldots, c_{jm_j}$ to the linguistic values $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ which describe each C_j (j=1,2,…,L). Each fuzzy system j, (j=1, 2,…, L) is a neural network containing a layer which combines linguistic values in order to form fuzzy preconditions and a layer which implements the fuzzy relation operated with the *max-min* composition. The weights in the fuzzy relation is adjusted to teachers' reasoning, in case where teachers' reasoning is available in the form of fuzzy IF-THEN, or is trained with a Hebbian-style learning approach [3], in case where teachers' reasoning is available in the form of examples.

Defuzzification Stage(stage 3): In the third stage, the fuzzy assessments cj= [$c_{j1}, c_{j2}, \ldots, c_{jm_j}$], (j=1, 2,…, L) (j=1, 2,…,L) are defuzzified to non-fuzzy values $C_{j1}, C_{j2}, \ldots, C_{jm_j}$ (j=1,2,…,L) of the learning characteristic Cj (j=1,2,…,L), by using a defuzzifier from the ensemble of the M defuzzifiers. depending on the number of linguistic values *mj* (*mj* >2) of each learning characteristic Cj (j=1, 2,…, L) a different defuzzifier is used. Each defuzzifier is a neural network, which is trained with a modified backpropagation algorithm that uses variable stepsize (called BPVS) [9].

3 Implementing the neural network-based fuzzy diagnostic model

3.1 The learning environment

The learning environment "Vectors in Physics and Mathematics" [5] is a discovery learning environment which has been designed and developed according to the constructivist theory of learning. The learning environment aims at helping teachers to instruct and students to construct the concepts of vectors in physics and mathematics in secondary schools. Each thematic unit contains several *scenarios*, which refer to real-life situations. Students carry out selected *activities* within these scenarios, which correspond to real world processes.

In order to implement the neural network-based fuzzy diagnostic model, we use the scenario “bodies in equilibrium” (figure 2) of the unit “Forces and Equilibrium. The environment resembles a simple mechanics- laboratory. A table appears on the screen and several objects such as boxes, cords, a spring and a pulley are available for use by the students. Several tools are also available, which help students draw and manipulate vectors representing forces, carry out measurements, etc. Students have the opportunity to carry out different equilibrium experiments by selecting one or two from the available objects from the object box and draw the forces acting upon each object them according to their conceptions. In figure 2 an example activity with two boxes on the table is shown. Students draw the forces acting on the box according to their opinions. They can then use the “test” button to observe the behavior of their model. For example, if the resultant force is not equal to zero, the box will move towards the direction of this force. Students can also click the “reality” button, in order to observe the scientific model, i.e. the representation of the correct forces acting on the box.

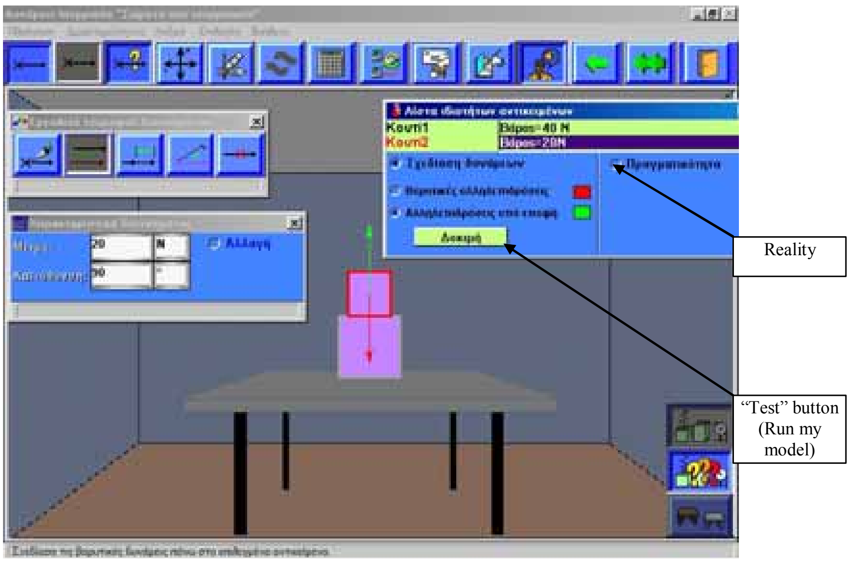

Fig. 2. Activity with a spring and a box

3.2 Implementing the neural network-based fuzzy diagnostic model to assess an aspect of the surface/deep approach of student learning

The deep/surface approach to learning is characterised by several defining features [10]. From these defining features, students' *intention to understand* and their *vigorous interaction with the content* were suggested by our group of experts. The two characteristics were labelled as *"student tendency to learn by discovery in a deep or surface way"* and assessed by the neural network-based fuzzy diagnostic model as the one and only characteristic C (L=1, therefore for simplicity C_j =C) described with five linguistic values (m =5) in the term set T(C) = $\{C_1, C_2, C_3, C_4, C_5\}$ = {*Deep, Rather Deep*, *Average*, *Rather surface*, *surface*}.

In order to elicit teachers' knowledge we have conducted an experiment with 18 students with the assistance of the group of expert teachers and students' interactions were recorded in the logfiles. The group of expert teachers suggested three linguistic variables B_1, B_2, B_3 associated with the scenario "Bodies in equilibrium": B_1="*the number of times a student tests his/her ideas or compares his/her ideas with -reality*", described with three linguistic values (f_1 =3) and by the term set $T(B_1)$= $\{V_{11}, V_{12}, V_{13}\}$ = {*Seldom, Sometimes, Frequently*} (see figure 3), B_2="*the number of times a student consults the dictionary or temporarily stops to think*", with f_2 =3 and $T(B_2)$= $\{V_{21}, V_{22}, V_{23}\}$ = {*Sometimes, Frequently, Always*}, B_3="*experiment carry out speed*", with f_3 =3 and $T(B_3)$ = $\{V_{31}, V_{32}, V_{33}\}$ ={*Fast, Medium, Slow*}. Using the real students' logfiles, we define with the assistance from the group of expert teachers, the membership functions $y_{i1}(x_i, m_i)$, $y_{i2}(x_i, m_i)$, $y_{i3}(x_i, m_i)$, $x_\iota \in U_\iota$, $m_i \in U_\iota$, $U_i \subset \Re^+$, (ι=1,2,3) of the linguistic values V_{i1}, V_{i2}, V_{i3} (ι=1,2,3) of each linguistic variable B_ι, (ι=1,2,3).

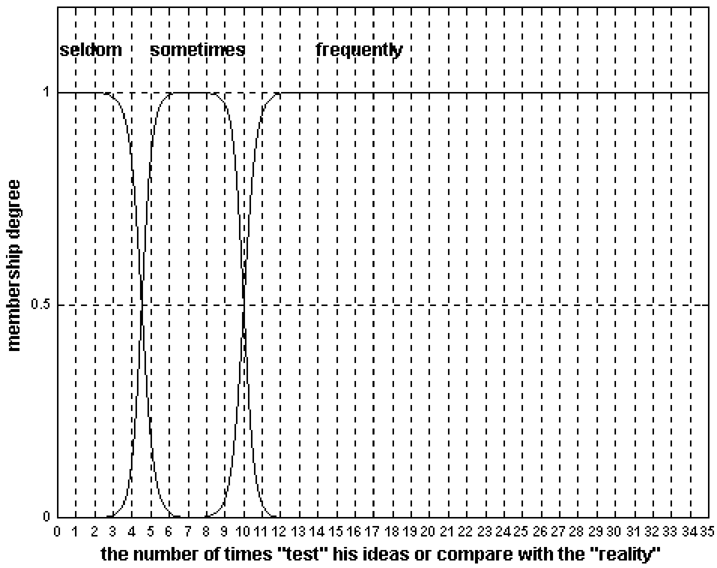

Fig. 3. Membership functions for the three linguistic values of the linguistic variable B_1 = *"the number of times a student tests his/her ideas or compares his/her ideas with reality"*

For example, as shown in figure 3, the universe of discourse U_1 of the linguistic variable B_1 = "*the number of times a student tests his/her ideas or compares his/her ideas with reality*", which is calculated from *the number of times* in each equilibrium experiment recorded in the logfiles, was set to [0, 35]. In the 18 students' logfiles, a threshold value of 2 times was found, since all students used the "Test" and "Reality" buttons once, regardless of whether they composed a successful or unsuccessful equilibrium experiment. Thus, 3 and 4 times have a large membership degree in the linguistic value V_{11} = "*seldom*", and the interval [4, 5] is the overlapping area of the membership functions $y_{11}(x_1) \quad x_1 \in [0,35]$ and $y_{12}(x_1) \quad x_1 \in [0,35]$ of the linguistic values V_{11} = "*seldom*" and V_{12} = "*sometimes*" respectively (Figure 3).

3.4. Training, testing and evaluating

In order to train and test the neural network-based fuzzy diagnostic model, a training set and three test sets of simulated students with predefined membership degrees $\{y_{11}, y_{12}, y_{13}\}$, $\{y_{21}, y_{22}, y_{23}\}$, $\{y_{31}, y_{32}, y_{32}\}$ to the linguistic values $\{V_{11}, V_{12}, V_{13}\}$, $\{V_{21}, V_{22}, V_{23}\}$, $\{V_{31}, V_{32}, V_{33}\}$, of the linguistic variables B_1, B_2, B_3 of their observable behavior B was generated and classified by the group of expert teachers with respect to their *"tendency to learn in a deep or surface way"* in one of the linguistic values of the term set T(C)= $\{C_1, C_2, C_3, C_4, C_5\}$ = {*Deep*, *Rather Deep*, *Average*, *Rather Surface*, *Surface*}. The first test set contains patterns with clear-cut descriptions of students' observable behavior B= {B_1, B_2, B_3}, i.e. their membership degrees $\{y_{i1}, y_{i2}, y_{i3}\}$, ($i$=1,2,3) in the linguistic values V_{i1}, V_{i2}, V_{i3}, (i=1,2,3) of each linguistic variable B_i (i=1,2,3) are close to 1. The second test set includes marginal cases, i.e. patterns that contain membership degrees $\{y_{i1}, y_{i2}, y_{i3}\}$, ($i$=1,2,3) close to 0.5 in two linguistic values V_{i1}, V_{i2}, V_{i3}, (i=1,2,3) of one or more than one linguistic variable B_i (i=1,2,3). This capability is usually not supported in a non-fuzzy rule-based environment. The third test set consists of special marginal cases, which are possible to cause conflicting judgments, if they are processed by means of classic IF-THEN rules.

The classifications of the group of experts were compared against the neural network-based fuzzy model classifications of the same simulated students for the three data sets. The overall average success in diagnosis reached 94%, i.e. 100%, 96%, 86% for each of the three data sets respectively. We also compared with the same training set and the same three test data sets the success in diagnosis of the neural network-based fuzzy model against two other approaches, namely a classic multilayer Neural Network (NN) trained with the backpropagation algorithm with variable stepsize [9], and a Fuzzified Neural Network (FNN) which is based on the ANFIS architecture, [8], with pseudotrapezoidal fuzzy sets. As shown in figure 4 the NN approach provides a diagnostic success of 84%, 82%, and 80% in the three data sets and the FNN was 100%, 98%, and 63% respectively. When we compare these results with the corresponding results of our model, it is clear our model provides improved performance in classifying the third test data set (special marginal cases).

Finally, the performance of our model has been evaluated in real classroom conditions during an experiment with an experienced physics teacher and 49 students attending physics lessons, providing satisfactory results as described in [15].

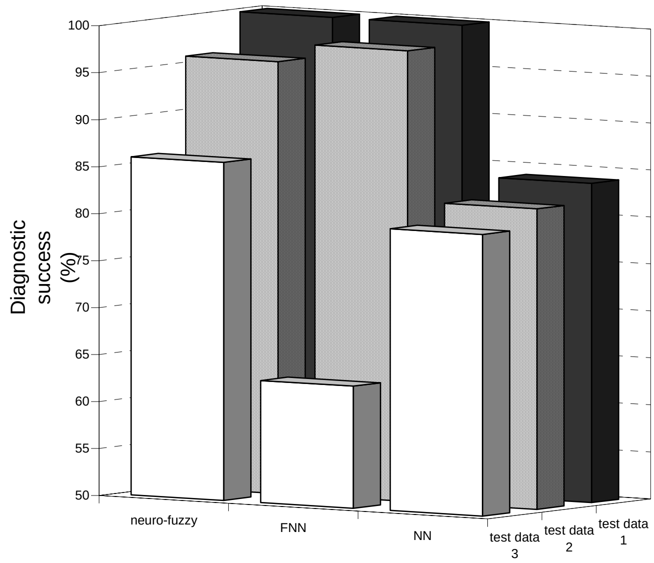

Fig. 4. Comparative results in the three test data

4 Conclusions and future work

In this thesis a neural network-based fuzzy diagnostic model is proposed to assess student learning characteristics and update the student model. A main advantage of the proposed model is that is a general diagnostic model which can be used to implement the diagnostic process in any learning environment according to designers' and teachers' suggestions. The proposed approach allows handling uncertainty of student behavior, by expressing teachers' qualitative knowledge in a clearly interpretable way with the use of fuzzy logic, while offering the possibility of adaptation to the learning environment and to teachers' personal constructs in classifying and discriminating among students by employing a neural network implementation of the fuzzy diagnostic model.

The neural network-based fuzzy diagnostic model has been tested in the discovery learning environment "*Vectors in Physics and Mathematics*" in diagnosing aspects of students' learning style. Experimental results of implementing, training and testing using the recommendations and expertise of a group of experienced teachers show that the proposed model manages the inherent uncertainty associated with human tutors' expertise in diagnosing aspects of students' learning style successfully, especially for marginal cases where our model accurately evaluates students by synthesizing conflicting assessments, providing better results than other neuro-fuzzy methods.

Further work which can be undertaken, in order to fully explore the benefits and limitations of the proposed approach include implementing the proposed model in diagnosing aspects of students' motivation and knowledge level, as well as implementing an authoring tool which allows teachers modify the adjusting parameters of the membership functions, as well as the weights in the fuzzy relations.

References

[1] Akhras F. N., Self J. A., (2002). Beyond intelligent tutoring systems: Situations, interaction, process and affordances. Instructional Science 30, 1-30.

[2] Conati C., Gertner A., & VanLehn K., (2002). Using Bayesian networks to manage uncertainty in student modeling, User Modeling & User-Adapted Interaction, 12 (4), 371-417.

[3] Dae-Sik J., and Hyung-Il C., (1997). Fuzzy Inference System Based on Fuzzy Associative Memory, Journal of Intelligent and Fuzzy Systems, Vol. 5, 271-284.

[4] Derry S. J., Potts M. K., (1998). How Tutors Model Students: A Study of Personal Constructs in Adaptive Tutoring. American Educational Research Journal. Spring 1998, Vol. 35, No 1, 65-99.

[5] Grigoriadou M., Mitropoulos D., Samarakou M., Solomonidou C., Stavridou E. (1999). Methodology for the Design of Educational Software in Mathematics and Physics for Secondary Education. Computer Based Learning in Science, Conf. Proc. 1999 pB3.

[6] Hawkes L.W., Derry S.J., (1996). Advances in Local Student Modeling Using Informal Fuzzy Reasoning, International Journal of Human-Computer Studies, 45, 697-722.

[7] Jameson A., (1996). Numerical Uncertainty Management in User and Student Modeling: An Overview of Systems and Issues. User Modeling and User-Adapted Interaction, 5, 193-251. Available on-line from: http://www.w5.cs.uni-sb.de/amp/home-page.html. Accessed at 20/01/2001

[8] Lin C-T, Lee G.C.S., (1995). Neural Fuzzy Systems: a Neuro-fuzzy Synergism to Intelligent Systems. Prentice Hall P T R, Upper Saddle River, NJ 07458

[9] Magoulas G.D., Vrahatis M.N., and Androulakis G.S., (1997). Effective back-propagation training with variable stepsize, Neural Networks, 10, 69-82

[10] Marton F., and Saljo R., (1997). Approaches to learning, in: F. Marton, D. Hounsell & N. Entwistle (Eds.), 2nd ed, The experience of learning, p. 36-55. Endinburg, UK: Scottish Academic Press.

[11] Pedrycz W., (1991). Neurocomputations in Relational Systems, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol 13, No 3, March 1991, 289-296.

[12] Posey C.L., Hawkes L.W., (1996). Neural Networks Applied to Knowledge Acquisition in the Student Model, Information Sciences 88, 275-298

[13] Sison R. and Shimura M. (1998). Student Modeling and Machine Learning International Journal of Artificial Intelligence in Education 9, 128-158.

[14] Stathacopoulou R., Magoulas G.D., Grigoriadou M., Samarakou M., (2005). Neuro-Fuzzy Knowledge Processing in Intelligent Learning Environments for Improved Student Diagnosis. Information Sciences, 170 2(4), 273-307.

[15] Stathacopoulou R., Grigoriadou M., Samarakou M., Mitropoulos D., (2006). Monitoring students' actions and using teachers' expertise in implementing and evaluating the neural network-based fuzzy diagnostic model, Expert Systems With Applications, in press, doi: 10.1016/j.eswa.2006.02.023

[16] VanLehn K (1988). Student Modeling. In M.C.Polson and J.J. Richardson (Eds). Foundations of Intelligent Tutoring Systems. Lawrence Elbaum, p. 55-78.

[17] Wenger E. (1987). Artificial Intelligence and Tutoring Systems, Computational and Cognitive Approaches to the Communication of Knowledge. Morgan Kaufmann.

[18] Zadeh L.A., (1989). Knowledge Representation in Fuzzy Logic, in Klir G.J. and Yuan B. (Ed), Fuzzy Sets Fuzzy Logic and Fuzzy Systems: Selected Papers by Lofti A. Zadeh, Advances in Fuzzy Systems-Application and Theory Vol 6, World Scientific, 1996.