J Inf Process Syst, Vol.13, No.1, pp.57~67, February 2017
https://doi.org/10.3745/JIPS.04.0011
ISSN 1976-913X (Print)
ISSN 2092-805X (Electronic)

JOURNAL OF INFORMATION PROCESSING SYSTEMS JIPS

An Intuitionistic Fuzzy Approach to Classify the User Based on an Assessment of the Learner's Knowledge Level in E-Learning Decision-Making

Mukta Goyal*, Divakar Yadav*, and Alka Tripathi**

Abstract

In this paper, Atanassov's intuitionistic fuzzy set theory is used to handle the uncertainty of students' knowledgeon domain concepts in an E-learning system. Their knowledge on these domain concepts has been collected from tests that were conducted during their learning phase. Atanassov's intuitionistic fuzzy user model is proposed to deal with vagueness in the user's knowledge description in domain concepts. The user model uses Atanassov's intuitionistic fuzzy sets for knowledge representation and linguistic rules for updating the user model. The scores obtained by each student were collected in this model and the decision about the students' knowledge acquisition for each concept whether completely learned, completely known, partially known or completely unknown were placed into the information table. Finally, it has been found that the proposed scheme is more appropriate than the fuzzy scheme.

Keywords

Domain Model, E-Learning, E-Learning Environment, Fuzzy Rules, Intuitionistic Fuzzy Set, User Modeling

1. Introduction

Personalization of the E-learning system depends on the learner's knowledge, background, and interests [1]. Learner modeling is a process in which information about the learner is collected and updated. Assessment is one of the strategic objectives of the E-learning system, which results in finding the value of the knowledge acquired by students [2]. Assessing a learner's knowledge level under uncertain conditions is not effective due to there being insufficient information available on the learner's responses to the test items [3]. Reliable student modeling comes via careful student assessment. It is the process that allows the expert to diagnose the learner's mental state and knowledge status in order to check the efficiency of teaching and to detect possible learning deficiencies [4]. An overlay model, which is a popular form of the structural model, represents the degree to which the user knows about a domain fragment [5]. Course sequences should facilitate input from not only content authors, but also from instructional designers and knowledge domain experts. Human decision-making can be modeled and simulated through soft computing approaches in an E-learning system [6,19]. Generalized nets are

Manuscript received October 18, 2013; accepted May 14, 2014; onlinefirst December 31, 2014.
Corresponding Author: Divakar Yadav (divakar.yadav@jiit.ac.in)
* Dept. of Computer Science & Engineering, Jaypee Institute of Information Technology, Noida 201307, Uttar Pradesh, India (mukta.goyal20@gmail.com, divakar.yadav@jiit.ac.in)
** Dept. of Mathematics, Jaypee Institute of Information Technology, Noida 201307, Uttar Pradesh, India (alka.choubey@gmail.com)

used as a tool for modeling to analyze the process of how universities function[7-15]. They are also used to analyze the process of administration, servicing, producing a timetable, the logical ordering of the subjects for students, and the assessment of students via Atanassov's intuitionistic fuzzy evaluations.

However, the objective of this paper is to assess user knowledge on the basis of an accumulative test and the updation of a user model. In a fuzzy set, the membership of an element is a single value between zero and one, but ina real life problem, it may not always be certain that the degree of non-membership of an element to a fuzzy set is equal to 1 minus the degree of membership. Due to the uncertain behavior of human beings, there may be some degree of hesitation. Therefore, Atanassov's intuitionistic fuzzy theory has been applied to assess the knowledge of the students.

2. Background Materials

This section is divided into four subsections. The first section describes the domain of the concepts, the second defines the user model, the third subsection describes how to deal with the uncertainty, and the fourth section describes some basic definitions that have been used in this work to apply Atanassov's intuitionistic fuzzy approach.

2.1 Domain Model

The domain model is a finite set of domain concepts that represents the entire teaching domain. The entire set of the domain is further partitioned into small elements or concepts, as shown in Table 1 for the subject of 'Automata Theory and Languages.' The numbers of such concepts represent the teaching domain and selected granularity. For example,a domain 'introduction to finite automata' is divided into smaller concepts like basic definitions, deterministic finite automata, nondeterministic finite automata, finite automata, etc., which can be described as $C=\{c_1,c_2\ldots, c_n\}$ where 'n' is the total number of domain concepts [16]. Learning dependencies amongconcepts are represented by the ordered prerequisite relation 'R,' as given below:

$$R \subseteq C \times C \tag{1}$$

$$R = \{(c_i, c_j): c_i \prec c_j;\ c_i,\ c_j \in C \tag{2}$$

Here, the prerequisite concept c_i is required to be known to the learner to be able to understand the second concept (*i.e.*, c_j). Thus, the learner can start learning the second concept only after learning the first one. After learning the domain concept of introduction to finite automata, a test is conducted to assess the learner's knowledge level. The knowledge of the teaching domain is represented in the domain model, which is one of the most important components of an adaptive system.

2.2 User Model

The user model describes the features of the learner, which are specific to each individual learner. The aspects that must be considered regarding the user model are as follows: what information about the user is included in the model and how is it obtained, representation of this information in the system and the process of forming and updating the model. The user model contains the information about the user, such as domain knowledge; learning performance; interests; preferences; goals; tasks; background; personal traits, such as learning style and aptitude; environment, such as the context of the work; and other useful features.

The content of the user model is divided into the two categories of domain specific information and domain independent information. Domain specific information reflects the status and degree of knowledge and skills that a student achieved ina certain subject. It is organized asa knowledge model that consists of many elements like concepts, topics, subjects, etc., that students are supposed to learn. The knowledge model can be created in the form of a vector model, overlay model, and fault model. Domain independent information includes goals, interests, background, experience, individual traits, aptitudes and demographic information.

In this work, overlay model has been applied to assess the learners' knowledge, a subset of domain model. The domain model is constructed by a set of knowledge elements that represent the knowledge of the expert. Each element represents a concept, subject or topic in the student's major. The user model is defined on the basis of an essential prerequisite concept that is necessary to perceive the selected concept in the same subdomain. Fig. 1 shows the related concept in the subdomain of context free language in the domain of the theory of automata.

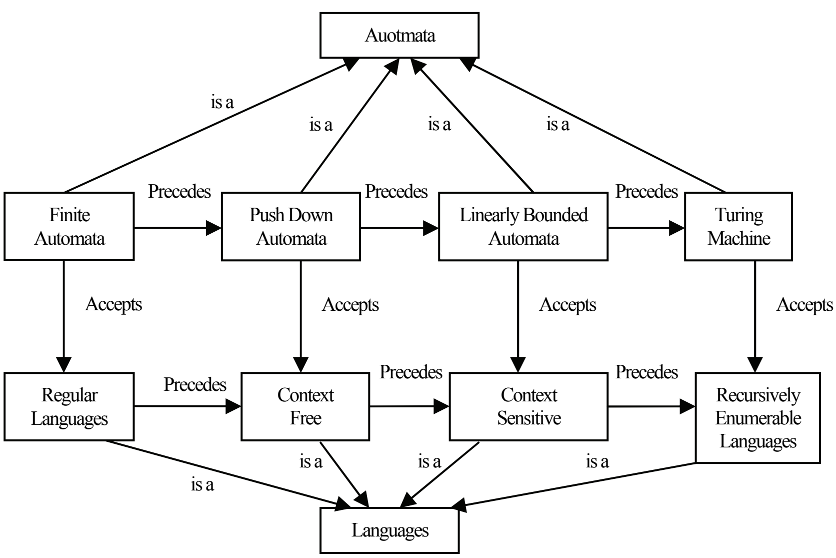

Fig. 1. Semantic net of the domain concept.

2.3 Dealing with the Uncertainty of Knowledge

Several approaches have been used to determine the uncertainty of the user's knowledge. Some examples of such approaches are rules that have certainty factors, fuzzy logic, and Bayes probability network, the Dempster-Shafer theory of evidence, Atanassov's intuitionistic fuzzy set theory, the intuitionistic fuzzy neural network and the neuro-fuzzy scheme. In most of the systems, an evaluation is done on the basis of the crisp response of the test taken by the user during the learning process. If the learner chooses an answer by guessing or chooses the most probable correct answer in multiple-choice questions,this leads to contributingto the uncertainty about the learner's knowledge. Few researchers [3] are dealing with the uncertainty of the learner's knowledge by using Atanassov's intuitionistic fuzzy set theory, in which the learner has the option of determining the percentage that he/she believes each answer to be correct in multiple-choice questions.

2.4 Brief Introduction to Atanassov's Intuitionistic Fuzzy Sets

The theory of intuitionistic fuzzy sets (IFSs) was introduced by Atanassov [17,20]in 1986. According to him, an intuitionistic fuzzy set defines a pair of membership andthe non-membership values. Here membership value is described as t_A and $f_A$is represented as a non-membership intuitionistic fuzzy value. Here t_A is represented as t and f_A as f.

Definition 1: An IFS A in X is an object that has the following form:

$$A = \{<x, t_A(x), f_A(x)> \mid x \in X\}$$

which is characterized by the membership function t_A and the non-member ship function f_A, where

$$t_A : X \to [0,1], x \in X \to t_A(x) \in [0,1] \tag{3}$$

$$f_A : X \to [0,1], x \in X \to f_A(x) \in [0,1] \tag{4}$$

with the condition: $t_A(x) + f_A(x) \leq 1$ for all $x \in X$ for each IFS A in X, if

$$\pi_A(x) = 1 - t_A(x) - f_A(x) \tag{5}$$

for all $x \in X$ then $\pi_A(x)$ is called the degree ofindeterminacy of x to A.It is a hesitancydegree of x to A, which is equal to:

$$0 \leq \pi_A(x) \leq 1 \text{ for all } x \in X$$

Atanassov's intuitionistic fuzzy set theory generalizes the fuzzy set theory [21] and hence all fuzzy sets are IFSs, but the converse is not necessarily true. IFS theory is beneficial in handling approximate and incomplete information and has been proved to be useful in various application areas of science and technology.

Definition 2: Let $a = (t, f)$ be an intuitionistic fuzzy value. The score function S can be evaluated as

$$S(a) = t - f, \quad S(a) \in [-1, 1] \tag{6}$$

Definition 3: Let $a = (t, f)$ be an intuitionistic fuzzy value. An accuracy function H of a can be evaluated as:

$$H(a) = t + f, \quad H(a) \in [0, 1] \tag{7}$$

According to Xu [18] the score function can be used to measure the intuitionistic fuzzy values. However, if the score values of two intuitionistic fuzzy values are equal, it is impossible to know which one is better. The relationship between the score function S and the accuracy function H, which is given below [22].

Table 1. Theory of automata concepts in knowledge domains

Chapter	Section	Subsection	Type of section	Concept
1. Introduction to Finite Automata				
	1.1 Basic Definitions	1.1.1 What is the alphabet 1.1.2 What are languages 1.1.3 What aredirected graphs 1.1.4 What areregular graphs	Learning Section	1.1_1 Intro to finite automata
	1.2 Test 1		Assessment Section	
	1.3 Deterministic Finite Automata		Learning Section	1.1_3 Intro to DFA
	1.4 Test 2		Assessment Section	
	1.5Non Deterministic Finite Automata	1.5.1 Construction of the NFA with a λ transition 1.5.2 Removal of a λ transition 1.5.3 The equivalence of NFA and DFA	Learning Section	1.1_5 Intro to NDFA
	1.6 Test 3		Assessment Section	
	1.7 Finite Automata with Outputs	1.7.1 Equivalence of Mealy and Moore machines	Learning Section	1.1_7 Intro to the Mealy and Moore machine
	1.8 Test 4		Assessment Section	

Definition 4: Let $a_1 = (t_1, f_1)$ and $a_2 = (t_2, f_2)$ be two intuitionistic fuzzy numbers, $S(a_1) = t_1 - f_1$ and $S(a_2) = t_2 - f_2$ be the score function of a_1 and a_2, respectively. Let $H(a_1) = t_1 + f_1$ *and* $H(a_2) = t_2 + f_2$ be the accuracy functions of a_1 and a_2, respectively, then:

If $S(a_1) < S(a_2)$, then a_1 is smaller than a_2, which is denoted by $a_1 < a_2$;

if $S(a_1) = S(a_2)$, then

If $H(a_1) = H(a_2)$ then a_1 and a_2 represent the same information, denoted by $a_1 = a_2$.

If $H(a_1) < H(a_2)$, then a_1 is smaller than a_2, denoted by $a_1 < a_2$;

If $H(a_1) > H(a_2)$, then a_1 is greater than a_2, denoted by $a_1 > a_2$;

Definition 5: Let $a_i = (t_i, f_i)$ $(I = 1, \ldots, n)$ be a collection of intuitionistic fuzzy numbers on X and let the intuitionistic fuzzy weighted averaging (IFWA) be $\Omega^n \rightarrow \Omega$, if:

$$IFWA_w(a_1,a_2,.....a_n,)=\prod_{i=1}^{n} a^{w_i} =(1-\prod_{i=1}^{n}(1-t_i)^{w_i},\prod_{i=1}^{n}(f_i)^{w_i}) \tag{8}$$

where $w=(w_1,w_2,....w_n)^T$ is the weight vector of $a_i(i=1,2,..n)$, and $w_i>0$, and $\sum_{i=1}^{n} w_i = 1$.

Here, user modeling is done on the basis of the assessment of the individual concept as Atanassov's intuitionistic fuzzy theory deals with the inaccurate information about the learner.

3. Methodology

In this work, Atanassov's intuitionistic fuzzy theory has been applied to assess the user on the basis of multiple-choice questions and the data is updated on the basis of the student's level of knowledge, which is collected in the student model. Multiple-choice questions have been used for assessing students' comprehension, which requires students to express their deeper understanding of the concepts. The steps listed below have been followed for to determine the student's knowledge and for updating the user.

3.1 Learner Assessment through Atanassov's Intuitionistic Fuzzy Approach

As shown in Table 1, after learning concept-1 (i.e., the introduction of the theory of automata), includes basic definitions and multiple-choice questions, which are designed to assess the learner's knowledge in the concept domain. Likewise, after learning each concept, a test is conducted for students to assess their knowledge in the concept domain. To deal with the uncertainty in the learner's knowledge, instead of taking the crisp input as a user response, the learner is given a choice to set the correctness percentage of each option. The sum of the correctness percentage should be less than or equal to 100. When the learner sets the correctness percentage for each of the options, the intuitionistic fuzzy score of i^{th} tested concept is denoted in the form of:

$$S_i=(t_i, f_i) \tag{9}$$

where S_i is the score of the i^{th} concept and t_i, f_i are the degree of the learner's understanding and lack of understanding the concept, respectively. t_i and f_i are calculated using Eqs. (10) and (11), respectively.

$$t_i = \frac{c_i}{100} \tag{10}$$

$$f_i = \frac{w_i}{100} \tag{11}$$

Here c_i is the correctness percentage that the learner assign to the correct option for multiple choice questions and w_i is the sum of correctness percentage that the learner assign to all incorrect options of the multiple choice questions.

3.2 Representing the User's Knowledge

The user's knowledge has been represented as an overlay model. These three fuzzy sets of *unknown*, *known* and *learned* concepts describe the user's knowledge of the domain concepts. A particular domain concept for user knowledge is expressed by providing values of membership functions and non-membership functions for the three intuitionistic fuzzy sets. The membership and non-membership functions are represented as:

$$(u(c),\ \mu_u(c),\ \upsilon_u(c)),\ (k(c),\ \mu_k(c),\ \upsilon_k(c)),\ (l(c),\ \mu_l(c),\ \upsilon_l(c)) \tag{12}$$

Where, $u(c)$, $k(c)$, $l(c)$ represent unknown, known and learned intuitionistic fuzzy sets respectively. $\mu_u(c)$, $\upsilon_u(c)$ represent the membership, and nonmembership values of unknown intuitionistic fuzzy set, $\mu_k(c)$, $\upsilon_k(c)$ represent the membership, and nonmembership values of known intuitionistic fuzzy set and $\mu_l(c)$,$\upsilon_l(c)$ represent the membership, and nonmembership values of the learned intuitionistic fuzzy set respectively.

3.3 The Updating of Knowledge through the Intuitionistic Fuzzy Set Theory

At beginning, the user's knowledge for each concept that he wants to learn is assumed completely unknown. Tests are used for checking the user's knowledge after every concept. After the user passes the test on one domain concept, then it is assumed that this concept has been learned. If the result is not satisfactory, the values of the variable concept knowledge are not updated. A new value of membership functions μ_L and υ_L for a set of learned concepts (completely learned) is based on the user'sanswers to the test questions. The intuitionistic fuzzy set theory method is used to describe the knowledge of a particular user for a specific concept. The user knowledge of each concept is described as the linguistic variable concept knowledge, which has five values: completely learned, partially learned, completely known, partially unknown and completely unknown. For all of these linguistic terms used in the intuitionistic fuzzy set, the membership function is defined, as shown below:

- Completely unknown= {0.20, 0.70}
- Partially unknown= {0.30, 0.50}
- Completely known ={0.50, 0.50,}
- Partially learned = {0.70, 0.20}
- Completely learned = {0.80, 0.10}

The following rules were been designed with respect to the linguistic terms stated above:

Rule 1: If concept c_i is unknown and concept c_j is completely unknown, then concept c_i remains unknown.

Rule 2: If concept c_i is partially unknown and concept c_j is partially unknown, then concept c_i is partially unknown.

Rule 3: If concept c_i is partially unknown and concept c_j is completely known, then concept c_i is partially known.

Rule 4: If concept c_i is partially unknown and concept c_j is completely known, then concept c_i is completely known.

Rule 5: If concept c_i is completely known and concept c_j is completely known, then concept c_i is completely known.

Rule 6: If concept c_i is partially unknown and concept c_j is partially learned, then concept c_i is completely known.

Rule 7: If concept c_i is partially learned and concept c_j is partially learned, then concept c_i is partially learned.

Rule 8: If concept c_i is partially learned and c_j is completely known, then concept c_i is partially learned.

Rule 9: If concept c_i is partially unknown and c_j is partially learned, then concept c_i is completely known.

Rule 10: If concept c_i is completely learned and c_j is partially unknown, then concept c_i is completely learned.

Rule 11: If concept c_i is not learned and concept c_j is learned, then concept c_i becomes learned.

Rule 12: If concept c_i is partially unknown and concept c_j is known, but not learned, concept c_i increases its known value.

Rule 13: If concept c_i is learned and concept c_j is learned, concept c_i increases its value of learned.

Rule 14: If concept c_i is completely known and concept c_j is completely learned, then concept c_i is completely learned.

Rule 15: If concept c_i is completely known and concept c_j is partially unknown, then concept c_i is completely known.

The degree to which concept c_i becomes known /learned depends on the values of known/learned for concept c_j, and the value of the prerequisite relation between both concepts is shown in Table 2.

This paper has considered two kinds of semantic relationships between the selected concept and the other concept of the knowledge domain, which are as follows: the prerequisite concept, which is necessary for perceiving the selected concept and the related concept, which is related to the selected concept and is in the subdomain. Hence, the membership function between the value of the prerequisite concept c_i and the related concept c_j is represented as $\mu_E(c_i,c_j)$. The level of the concept c_i becomes known/learned, depending on the known/learned values for the concept c_j and the value of the prerequisite relation between both concepts. The actual values of the intuitionistic membership functions $\mu_k(c_i)$ and $\mu_L(c_i)$ are calculated from the values of membership functions $\mu_k(c_i)$, $\mu_L(c_i)$ and $\mu_E(c_i,c_j)$.

Some of the rules do not change the values of $\mu_u(c_i)$, of $\mu_k(c_i)$ and of $\mu_l(c_i)$. For some rules, the new values of membership are calculated using:

$$\mu_k(c_i) = \mu_E(c_i, c_j).\mu_k(c_j); \upsilon_k(c_i)=\upsilon_E(c_i, c_j).\upsilon_k(c_j) \tag{13}$$

$$\mu_L(c_i) = \mu_E(c_i, c_j).\mu_L(c_j); \upsilon_L(c_i)=\upsilon_E(c_i, c_j).\upsilon_L(c_j) \tag{14}$$

$$\mu_k(c_i)=max[\mu_k(c_i),\mu_E(c_i, c_j).\mu_k(c_j)]; \upsilon_k(c_i)=min[\upsilon_k(c_i), max[\upsilon_E(c_i, c_j).\upsilon_k(c_j)]] \tag{15}$$

$$\mu_L(c_i)=max[\mu_L(c_i),\mu_E(c_i,c_j).\mu_L(c_j)]; \upsilon_L(c_i)= min[\upsilon_L(c_i), max[\upsilon_E(c_i,c_j).\upsilon_L(c_j)]] \tag{16}$$

In Eqs. (15) and (16), max functions have been used for merging the two values of the membership functions. According to our user model, the user's knowledge of the concept can only increase.

Table 2. Decision table for testing the prerequisite concept of Basic Definition and the related concept for Deterministic Finite Automata on the basis of the intuitionistic fuzzy logic for learners

Learner	Score 1 (C1)	Score 2 (C2)	Decisionlevel
S1	(0.5, 0.5)	(1, 0)	C_i is completely learned
S2	(0.378, 0.522)	(0.655, 0.245)	C_i is completely known
S3	(0.19, 0.71)	(0.235, 0.665)	C_i is unknown
S4	(1, 0)	(1, 0)	C_i is learned
S5	(0.152, 0.748)	(1, 0)	C_i is completely learned
S6	(0.547, 0.353)	(1, 0)	C_j is completely learned
S7	(0.678, 0.272)	(0.321, 0.579)	C_j is completely known

4. Conclusion

In this work, Atanassov's intuitionistic fuzzy theory has been applied to handle the inaccurate information from the user who takes the test and deals with the uncertainty of the user's knowledge. The IFS theory of domain concepts is used for describing the user's knowledge through the linguistic rules and these linguistic rules update the user model. The risk associated with this method is that if the learner chooses options such that the sums of the percentage of correct options turns out to be 100 in all of the questions, then the system will determine the learner's knowledge via the learner's crisp responses to the tests that are taken during the learning process. If this occurs, then the method of applying the IFS theory to handle inaccurate information about the learner will fail. A personalization of learning materials in an E-learning environment can be provided through a user model on the basis of test score on domain concept.

References

[1] P. Brusilovsky, "Methods and techniques of adaptive hypermedia," *User Modeling and User-Adapted Interaction*, vol. 6, no. 2-3, pp. 87-129, 1996.

[2] R. Barchino, J. M. Gutierrez, S. Oton, J. J. Martinez, J. R. Hilera, and J. A. Gutierrez, "E-Learning model for assessment," in *Proceedings of the IADIS Virtual Multi-conference on Computer Science and Information Systems (MCCSIS2006)*, 2006, pp. 1-5.

[3] R. Hosseini and A. Kardan, "Intuitionistic fuzzy-based method for assessing the learner's knowledge level and personalization of learning path," in *Proceedings of the 6th International Conference on Virtual Learning (ICVL2011)*, Cluj-Napoca, Romania, 2011, pp. 441-447.

[4] A. S. Drigas, K. Argyri, and J. Vrettaros, "Decade review (1999-2009): artificial intelligence techniques in student modeling," in *Proceedings of the 2nd World Summit on the Knowledge Society (WSKS 2009)*, Chania, Greece, 2009, pp. 552-564.

[5] P. Brusilovsky and E. Millan, "User models for adaptive hypermedia and adaptive educational systems," in *The Adaptive Web*. Heidelberg: Springer, 2007, pp. 3-53.

[6] E. Frias-Martinez, G. Magoulas, S. Chen, and R. Macredie, "Recent soft computing approaches to user modelling in adaptive hypermedia," in *Adaptive Hypermedia and Adaptive Web-Based Systems*. Heidelberg: Springer, 2004, pp. 104-114.

[7] A. Shannon, D. Langova-Orozova, E. Sotirova, I. Petrounias, K. Atanassov, M. Krawszak, P. Melo-Pinto, T. Kim, and V. Tasseva, "A generalized net model of the separate information flow connections within a university," in *Proceedings of the 3rd International IEEE Conference on Intelligent Systems*, London, 2006, pp. 760-763.

[8] A. Shannon, K. Atanassov, D. Langova-Orozova, M. Krawczak, E. Sotirova, P. Melo-Pinto, I. Petrounias, and T. Kim, *Generalized Net Modelling of University Processes*. North Sydney: KvB Institute of Technology, 2005.

[9] D. Dimitrakiev, S. Sotirov, E. Sotirova, D. Orozova, A. Shannon, and H. Panayotov, "Generalized net model of process of the administration servicing in a digital university," in *Proceedings of the 14th International Conference on Intuitionistic Fuzzy Sets (ICIFS2010)*, Sofia, Bulgaria, 2010, pp. 50-56.

[10] A. Shannon, E. Sotirova, K. Atanassov, M. Krawczak, P. Melo-Pinto, S. Sotirov, and T. Kim, "Generalized net model of the process of ordering of university subjects," in *Proceedings of the 7th International Workshop on Generalized Nets*, Sofia, Bulgaria, 2006, pp. 25-29.

[11] A. Shannon, D. Orozova, E. Sotirova, K. Atanassov, M. Krawczak, P. Melo-Pinto, R. Nikolov, S. Sotirov, and T. Kim, "Towards a model of the digital university: a generalized net model for producing course timetables," in *Proceedings of the 4th International IEEE Conference on Intelligent Systems*, Varna, Bulgaria, 2008, pp. 16-25.

[12] A. Shannon, K. Atanassov, B. Riecan, M. Krawczak, D. Orozova, P. Melo-Pinto, E. Sotirova, R. Parvathi, and T. Kim, "Generalized net model of the process of selection and usage of an intelligent e-Learning system," in *Proceedings of the 6th IEEE International Conference on Intelligent System*,Sofia, Bulgaria, 2012, pp. 233-236.

[13] A. Shannon, E. Sotirova, K. Atanassov, M. Krawczak, P. Melo-Pinto, and T. Kim, "Generalized net model of lecturer's evaluation of student work with intuitionistic fuzzy estimations," in *Proceedings of the 2nd International Workshop on Intuitionistic Fuzzy Sets*, Banska Bystrica, Slovakia, 2006, pp. 22-28.

[14] A. Shannon, B. Riecan, E. Sotirova, G. Inovska, K. Atanassov, M. Krawczak, P. Melo-Pinto, and T. Kim, "A generalized net model of university subjects rating with intuitionistic fuzzy estimations," in *Proceedings of the 16th International Conference on Intuitionistic Fuzzy Sets (ICIFS2010)*, Sofia, Bulgaria, 2012, pp. 61-67.

[15] E. Sotirova, "Classification of the student's intuitionistic fuzzy estimations by a 3-dimensional selforganizing map," in *Proceedings of the 7th International Workshop on Intuitionistic Fuzzy Sets*, Banska Bystrica, Slovakia, 2011, pp. 64-68.

[16] E. Andres, R. Fleischer, and M. Liang, "An adaptive theory of computation online course in ActiveMath," in *Proceedings of the 5th International Conference on Computer Science & Education (ICCSE2010)*, Hefei, China, 2010, pp. 317-322.

[17] K. T. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets and Systems*, vol. 20, no. 1, pp. 87-96, 1986.

[18] Z. Xu, "Intuitionistic fuzzy aggregation operators," *IEEE Transaction on Fuzzy Systems*, vol. 15, no. 6, pp. 1179-1187, 2007.

[19] R. D. Nielsen, W. Ward, and J. H. Martin, "Soft computing in intelligent tutoring systems and educational assessment," in *Soft Computing Applications in Business*. Heidelberg: Springer, 2008, pp. 201-230.

[20] K. T. Atanassov, "Intuitionistic fuzzy sets, past, present and future," in *Proceedings of the 3rd Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT2003)*, Zittau, Germany, 2003, pp. 12-19.

[21] L. A. Zadeh, "Outline of a newapproach to the analysis of complex systems and decision processes interval valued fuzzy sets," *IEEE Transaction on Systems, Man and Cybernetics*, vol. SMC-3, no. 1, pp. 28-44, 1973.

[22] D. H. Hong and C. H. Choi, "Multicriteria fuzzy decision-making problems based on vague set theory," *Fuzzy Sets Systems*, vol. 114, pp. 103–113, 2000.

Mukta Goyal

She is pursuing her Ph.D. (CSE) from Jaypee Institute ofInformation Technology, Noida. She received her under Graduation (CSE) from Govt. college of engineering, Trivandrum, Kerala University and Masters (CSE) from Banasthali University. She has more than 12 years of teaching experience. Her area of research is E-learning and AI.

Divakar Yadav

He received his Ph.D. degree in Computer Science and Engineering from Jaypee Institute of Information Technology, Noida, India in Feb 2010. He spent one year, from Oct 2011 to Oct 2012, in Carlos III University, Leganes, Madrid, Spain as a post doctoral fellow. He has published more than 40 research papers in reputed international/national journals and conference proceedings. His areas of interest are Information retrieval and soft computing.

Alka Tripathi

She at present is a Professorat Jaypee Institute of Information Technology (Deemed to be Univerisity), Noida. She received her Ph.D. (Mathematics) degree from Banaras Hindu University, Varanasi. She has published more than 25 research papers in reputed international/national journals and conference proceedings. Her area of research is Fuzzy Topology and Fuzzy Automata Theory.