

The Concurrent Method of Personalised e-learning Path Evaluation

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Abstract — *The following aspects as: the presentation mechanisms (IMS), the course tree and the graph structures (SCORM, MAMS) and interoperability (Common Cartridge action) have become leading standards of e-learning. However, the personalisation processes (units structure finding) and its' on-line evaluation are still an open area for the research. The composed individual path allows us to meet the users' demands; although the path accuracy for a specific user is usually examined after the full lesson cycle. The invalid path can discourage the user from either the learnt topic or the system in general. The paper introduces the concurrent method of evaluation of user's results, within lesson, based on pre-defined expectations function. This method helps to pick the invalid path and recommend it for re-evaluation if needed.*

Index Terms — *LMS, cognitive models, learning system, path selection.*

INTRODUCTION

The both structure and organisation of electronic courses were defined by various specifications and they are controlled by the Learning Management Systems (LMS) [8] [9] [10] [11]. The training applications (e-content) are developed in fundamentals of various theories [2] [3] [6] [10] based on different forms: linear paths, branched trees, blocks, sequences and complex graphs.

The training courseware consists of fundamental units called frames (SCO, the smallest organisation data-unit) [5] [6] [11]. Frames are presented to a user as a learning path in accordance with given standard.

Majority of the LMS systems [2][4][7][12] estimate knowledge by simple measures expressed in percentage from 0% to 100% as a result of single or multiple choice answers.

The proposed method gives a background expectation for given lesson path and user. Based structure as well as characteristic features set has to be defined to create the expectation function of user's progress, which will be described next in details. Finally surveys and future works discussion is presented.

GRAPH STRUCTURE AND FEATURES DEFINITION

A fundamental part of the e-learning system is a database containing all relations of the e-content units [15] and profiles describing current skills of users. Courses vocabulary relations are usually defined as a tree structure, as in the example solution available in SCORM standard [4] [5] [6]. The structures are based on semantic descriptors, used in majority thesauruses and syllabuses, using RDF [21] [22] (Resource Description Framework), XOL (ontology exchange language) [18] or many other formats [17] [19] [20].

Structure definition

The described standard relations can be represented as unified directed multi-graph [1] [13] [14]:

$$G = (V, E) \quad (1)$$

where:

$V = \{v_1, v_2, \dots, v_n\}$, is a set of vertices identified with system objects,

$E = \{e_1, e_2, \dots, e_n\}$, is a set of edges, which describes vertices mutual relations.

Vertices within the directed multi-graph are divided into four separate sets, according to the defined layers (B):

$$V = R \cup T \cup U \cup O \quad (2)$$

$$R \cap T = R \cap U = T \cap U = R \cap O = T \cap O = U \cap O = \emptyset \quad (3)$$

where:

R - finite set of objects, which represents e-content frames stored in system:

$$R = \{r_1, r_2, \dots, r_k\} \quad (4)$$

T - finite set of objects; which represents information gathered in frames, described by semi-natural language:

$$T = \{t_1, t_2, \dots, t_m\} \quad (5)$$

U - finite set of objects, which represents system's users:

$$U = \{u_1, u_2, \dots, u_n\} \quad (6)$$

O - finite set of objects, which represents frames' evaluation mechanisms:

$$O = \{o_1, o_2, \dots, o_n\}$$

Directional multi-graph assigns an edge for ordered pair of vertices:

$$G : e_i \Rightarrow B \times B \quad (7)$$

Edges of the graph are based on Cartesian product of two layers (sets). Relations of the Cartesian square product of vertices of the same layer are called internal, otherwise they are called external; defined as:

$$\begin{aligned} E_{B \times B} &: \{(v_i, v_j) : (v_i, v_j) \in B \times B\} \\ C_{B \times B} &= \{c_1^{B \times B}, c_2^{B \times B}, \dots, c_c^{B \times B}, \dots, c_{c_{\max}}^{B \times B}\} \\ P_{c_{B \times B}} &= \{p_1, p_2, \dots, p_p, \dots, p_{p_{\max}}\} \\ {}^e f_{B \times B} &: E_{B \times B} \times C_{B \times B} \rightarrow \{p_i : p_i \in P_{c_{B \times B}}\} \\ \lambda_{B \times B} &: C_{B \times B} \rightarrow a : a = [0, 1] \end{aligned} \quad (8)$$

where:

- $E_{B \times B}$ - edge defined as ordered pair of vertices,
- ${}^e f$ - default function, assigns value p_{c_j} for edge e_i and feature c_j ,
- $C_{B \times B}$ - finite set of features (attributes) for Cartesian product (layers $B \times B$),
- $P_{c_{B \times B}}$ - values set for distinct attributes. Values are within $[0, 1]$ range,
- λ - quality function, defines influence on evaluation and lesson selection process (default '1') of a feature.

Treating vertices features as internal edge functions allows us to simplify the application structure into just one class of features (all the discriminated features were described already in many works [13] [14]. This paper will be presenting only those features, which are used by the described method.

Evaluation features

The layer R contains the application part - fundamental unit:

- the frame identifier,
- evaluation methods,
- relation within the application objects (layers T, O and U).

Implemented statistics allow using more complex evaluation methods. Each frame can be measured by many O layer objects. Values returned from the evaluation objects : $\{p_1, p_2, p_3, p_4, p_5, \dots, p_n\}$, are taken under account while defining overall frame grade used in proposed method; evaluated as:

$${}^e f_{framegrade}(u_j, r_i) = \frac{\sum_{i=1}^n \lambda_i p_i}{\sum_{i=1}^n \lambda_i} \quad (9)$$

User statistical profile

Layer U defines the users' data record; with their preference and skills. First two features: the user type (wo) and knowledge level (ts) defines the main user's measures; by function:

$${}^e f_{wo} \begin{cases} 0.99 : \text{expert} \\ 0.6 : \text{teacher} \\ 0.1 : \text{student} \end{cases}$$

The wo value is predefined in system. Second value (ts) is evaluated in a fuzzy reasoning process. The profile features are generated based on statistics estimation [16]. The most representative mean values were extracted from the system:

- grade arithmetic mean,
- grade geometric mean, illustration of increasing user's knowledge,
- dominant feature, showing the most frequent user grade,
- quartile, first and third, for the grade distribution

As well as variety of additional measurements:

- variety domain, shows the results reliability,
- variance that shows the average knowledge deviation,
- asymmetric and concentration measures, assigning the user's abilities to drive into lower or higher grades.

User's profile contains valuable data for a reasoning process. Measurements are performed based on all user results history. Additionally, measures for given topic defined by t_y term (within lessons) are generated. Term measures must fulfil following equation:

$${}^e f_{measure}(u_j, t_y) = {}^e f_{measure}(u_j, u_j) : \forall r_x \in R, \exists c f_c(t_y, r_x) \neq 0 \quad (10)$$

The User's reliability measure

Relations of the system graph G, are under constant evaluation procedures by a fuzzy controller (figure 1).

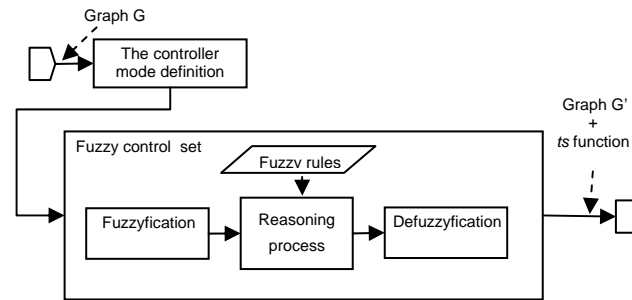


FIGURE 1
FUZZY CONTROLLER

The conclusion making unit is controlled by two data streams. The first one provides all system data, the second one conclusion rules. The fuzzy reasoning are executed for the ts feature value estimation [23] [24], according to the fuzzy controller settings. Every conclusion feature is defined as a fuzzy set A of values $z \in [0, 1]$, in a normalised range, defined as a set:

$$A = \{(z, \mu_A(z)); z \in [0,1]\}$$

where:

$$\mu_A : Z \rightarrow [0;1]$$

The values of membership function (μ_A) are defined in ranges of following relations:

- $\mu_A(z) = 1$, means full membership of the set A of fuzzy values; $z \subset A$,
- $\mu_A(z) = 0$, z is not belonging to the set; $z \notin A$,
- $0 < \mu_A(z) < 1$, defines partial membership of the element z in the set A.

Conclusions based on more than one feature are assigned by the fuzzy set operations [23].

The *product* (AND), being an intersection of fuzzy sets $A', A'' \in A$, according to regulations of T- norm:

$$\mu_{A' \cap A''}(z) = TN(\mu_{A'}(z), \mu_{A''}(z));$$

is used for calculations:

$$TN(\mu_{A'}(z), \mu_{A''}(z)) = \min(\mu_{A'}(z), \mu_{A''}(z)).$$

The logical OR function, as an S-norm:

$$\mu_{A' \cup A''}(z) = SN(\mu_{A'}(z), \mu_{A''}(z)),$$

is used for fuzzy sets ($A', A'' \in A$) addition; to simplify calculations:

$$SN(\mu_{A'}(z), \mu_{A''}(z)) = \max(\mu_{A'}(z), \mu_{A''}(z)).$$

The object's values are described by trapezoid membership functions [22] using four coefficients: a, b, c and d (figure 2):

$$\mu_A^{abcd}(z) = \begin{cases} \frac{z-a}{b-a} & \text{for } b > z > a \\ 1 & \text{for } c \geq z \geq b \\ \frac{d-z}{d-c} & \text{for } d > z > c \\ 0 & \text{for } z \leq a \vee z \geq d \end{cases}$$

In case the linguistic variables for characteristic features are not defined, variables: low, medium and high are defined by default (figure 2).

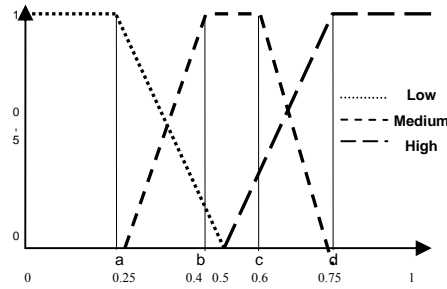


FIGURE 2

THE LINGUISTICS VARIABLES IN FUZZY DECISION SETS A AND A' MEANING

The evaluation accuracy is controlled by a number of linguistic variables. The defined fuzzy sets and conclusion rules are working in accordance with modus ponens theorem. For the conclusion making algorithm, the Zadeh rule are used [25]:

$$\mu_{A \rightarrow A'}(z, z') = \max\{\min[\mu_A(z), \mu_{A'}(z')], 1 - \mu_A(z)\}$$

The new *ts* value is obtained by evaluation procedures. From several often used computation methods sums of centres' and gravity centres' analysis were carried on. Finally, the method of the gravity centres was implemented, as:

$$\bar{z}_i' = \frac{\sum_{k=1}^N \mu_{A'^k}(z_i') z_i'}{\sum_{k=1}^N \mu_{A'^k}(z_i')}$$

The *ts-p* is a previous value of *ts* feature. The *re-eval* feature (by default 0,5) returns 1 value for underestimation of user's progress or returns 0 for overestimation of user's progress (figure 5). To evaluate the user's reliability, the following rule set are used:

The first estimation within the lesson path:

- if 're-eval'(u_j, u_j) is medium and ('dominant'(u_j, u_j) is low or 'mean'(u_j, u_j) is low) then 'ts'(u_j, u_j) is low
- if 're-eval'(u_j, u_j) is medium and 'dominant'(u_j, u_j) is medium and 'variance'(u_j, u_j) is high then 'ts'(u_j, u_j) is low
- if 're-eval'(u_j, u_j) is medium and 'dominant'(u_j, u_j) is medium and ('variance'(u_j, u_j) is low or 'variance'(u_j, u_j) is medium) then 'ts'(u_j, u_j) is medium
- if 're-eval'(u_j, u_j) is medium and 'dominant'(u_j, u_j) is high or 'mean'(u_j, u_j) is high then 'ts'(u_j, u_j) is medium
- if 're-eval'(u_j, u_j) is medium and ('wo'(u_j, u_j) is medium or 'wo'(u_j, u_j) is high) and 'variance'(u_j, u_j) is low then 'ts'(u_j, u_j) is high

The re-estimation within the lesson:

- if 're-eval'(u_j, u_j) is low and 'ts-p'(u_j, u_j) is medium then 'ts'(u_j, u_j) is low
- if 're-eval'(u_j, u_j) is low and 'ts-p'(u_j, u_j) is high then 'ts'(u_j, u_j) is medium
- if 're-eval'(u_j, u_j) is high and 'ts-p'(u_j, u_j) is low then 'ts'(u_j, u_j) is medium
- if 're-eval'(u_j, u_j) is high and 'ts-p'(u_j, u_j) is medium and 'wo'(u_j, u_j) is high then 'ts'(u_j, u_j) is high
- if 're-eval'(u_j, u_j) is high and 'ts-p'(u_j, u_j) is medium and 'dominant'(u_j, t_j) is high and 'variance'(u_j, t_j) is low then 'ts'(u_j, u_j) is high

PROPOSED MODEL

The automatic process' evaluation requires analysis of the flow of signals between user, teacher and computer. Based on mutual relation of signals (defined on the figure 3) the function of user's real and estimated progress was defined according to the classic Cybernetic model.

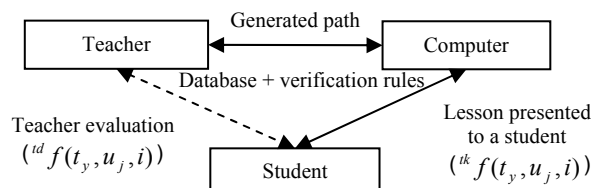


FIGURE 3

SUBJECTS' RELATION WITHIN SYSTEM

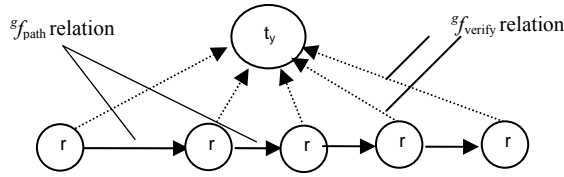


FIGURE 4
THE GENERATED LESSON PATH

The teacher, in systems like SCORM or MOODLE, defines a strict path between each frame under changing conditions. All changes in their organisation structure must be pre-defined. In the proposed method strict evaluation is exchanged by the progress function, based on the lesson graph (figure 4), for a given user and a given term realized in the n-step path:

$${}^{iw}f(t_y, u_j, i) = {}^{iw}f(t_y, u_j, i-1) + {}^{tk}f(t_y, u_j, i) + {}^{td}f(t_y, u_j, i) \quad (11)$$

where:

- i - is an index of a current frame ,
- ${}^{iw}f(t_y, u_j, 0)$ - defines the user progress (knowledge) in given subject, before the lesson starts, usually equal to the $e_{f_{grade}}(t_y, u_j)$,
- ${}^{tk}f(t_y, u_j, i)$ - defines the progress of a lesson measured by a computer,
- ${}^{td}f(t_y, u_j, i)$ - defines the verification of a teacher .

This model is a discreet one, according to the closed frames (SCO) structure. The measure for real progress is defined as:

$${}^{tk}f(t_y, u_j, i) = e_{f_{framegrade}}(u_j, r_i) \cdot {}^l f_{verify}(r_i, t_y) \quad (12)$$

The estimated progress of the user is proportional to the ts feature defined in the previous step:

$${}^{tk}f(t_y, u_j, i) = \max(e_{f_{ts}}(u_j, u_j), f_{wo}(u_j, u_j)) \cdot {}^l f_{verify}(r_i, t_y) \quad (13)$$

Function ${}^{td}f$ in case of real user progress returns always 0 value. However, ${}^{td}f(i)$ for expectation function expresses the accepted error range for the optimal path flow; defined as follows:

$$err_rate = \max(e_{f_{variance}}(u_j, u_j), \frac{1 - e_{f_{ts}}(u_j, u_j)}{2}) \quad (14)$$

$${}^{td}f(t_y, u_j, i) = (-{}^l f_{verify}(r_i, t_y) err_rate, +{}^l f_{verify}(r_i, t_y) err_rate)$$

The estimation function for a example path is presented in figure 5.

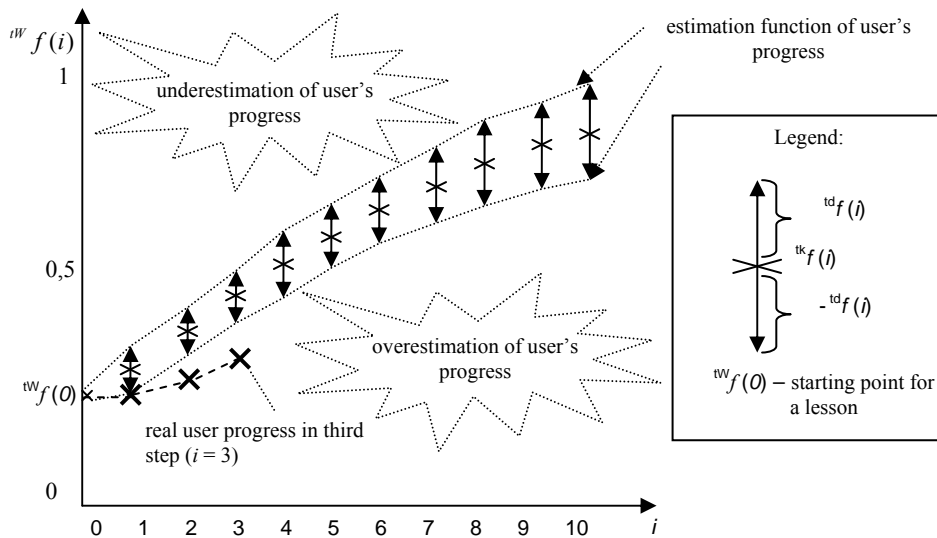


FIGURE 5
THE USER LESSON ESTIMATION PROGRESS

The method compares the user's real progress to the estimation made by the system. If user's progress does not meet requirements, the current lesson path is recommended to re-evaluate. However, the final decision belongs to the user.

EXPERIMENTS AND SUMMARY

Two laboratory experiments with a group of 10 students were conducted. In the first experiment (for IT fundamentals) two student groups were either learning, using the system, without prediction function or with it. A group with the re-evaluation possibility achieved 7 % higher results.

The second survey was conducted using one group of students. The students were asked, after full lesson cycle, if re-evaluation of lesson was helpful. 80% of students said it was a positive improvement.

The elaborated function simplifies the applications' development process. It was empirically verified, with its' all controlling mechanisms; using all multilayered facilities (introduced for the first time by Kay's works many years ago).

Next step is to test the function empirically on wider student population, extending its possibilities to evaluate the type of a preferred learning approach.

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