ADAPTIVE E-LEARNING SYSTEMS WITH CONCEPT MAPS

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Rezumat: Sistemele adaptabile de e-Learning reprezintă o nouă paradigmă în metodele moderne de învățare. Ele nu se bazează doar pe asigurarea unei cantități mari de informații ci □i pe calitatea transferului de cunoştințe. În acest sens este esențială identificarea corectă a stilului de învățare al fiecărui utilizator pentru a i se oferi un conținut adecvat. În plus, o reevaluare continuă şi o clasificare sunt importante pentru a face față progreselor realizate în timpul procesului de învățare şi pentru a asigura o mai bună evoluție. Hăr□ile conceptuale sunt un instrument important atât în dezvoltarea unui conținut de înaltă calitate cât şi pentru evaluarea automată. Această lucrare prezintă un model pentru un sistem adaptabil de e-Learning şi detaliază modulele responsabile cu identificarea tipului de utilizator şi a hărților conceptuale.

Cuvinte cheie: sistem adaptabil de e-Learning, stil de învățare, hărți conceptuale, grupare, hărți autoorganizat

Abstract: Adaptive e-learning systems represent a new paradigm in modern learning approaches. They are not only targeting curricula segmentation, as providing large quantities of content is not the ultimate goal, but focus on the quality of knowledge transfer. In doing so, the correct identification of the user learning style in order to provide the appropriate content presentation to each individual user is essential. Moreover, a continuous re-evaluation and classification is important to cope with the progress made during the learning process, and to ensure the evolution to a better style. Concept maps represent useful instruments in both developing quality high structured content and automated evaluation. This paper presents a model for an adaptive e-learning system, and details the modules responsible for the user type identification and concept maps.

Keyword: Adaptive e-learning, learning style, concept maps, clustering, self-organizing maps.

1. Introduction

Following current trends triggered by the evolution of the technology, the education process has started to shift from the traditional face-to-face instruction to more modern approaches, such as online education, with the advantage of being available anywhere, anytime. The purpose of adaptive e-learning systems is to increase the student's performance by adjusting the content and interaction methods to users with different interests, initial knowledge, background and skills. When confronted with the task of defining the user model, the developers of e-learning platforms rely on learning theories from educational psychology and pedagogy. There are some habitual ways of identifying user styles such us: answers to psychological tests and behavioral data observed from user interaction with the e-learning platforms. Current trends focus on the design of e-learning systems that contribute to the improvement the user's performance during the learning process. The goal is no longer the acquisition of knowledge alone, but how to do it in the most appropriate manner for each individual.

Most of the online training systems are based on curricula segmentation, situation in which the students must go through a predefined structure. It is widely acknowledged that the student should be involved actively in the online learning process and that e-learning systems should sustain the student’s control and organization upon information [13]. Thus, the online training systems should constrain the user less, and should be able to adjust on his/her characteristic learning style. An essential element is anticipating the students' behavior and adapting the content (both quantitatively and qualitatively) according to the needs. Thus, the structure of the courses and the segmentation of their presentation must be personalized according to the type of student.

An intelligent system should adjust the content in order to ensure faster learning and better performance. Moreover, it should help students develop new, desirable learning abilities.

This paper presents an efficient and accurate method for identifying the user typology in adaptive e-learning systems, and an original technique for automated evaluation of the knowledge acquired, using concept maps. The rest of the paper is organized as follows: section II presents the state of the art in adaptive e-learning systems; section III is a brief overview on the theory of learning styles, with focus on adaptive systems; section IV presents the general design of our proposed model for an adaptive e-learning system. Section V details the intelligent module, responsible for static and dynamic user type identification, while section VI presents the concept map paradigm, with focus on our method for automated evaluation of concept maps. The concluding remarks and future directions are presented in section VII.

2. Existing e-learning Systems

In traditional education, many of the prescriptions formulated by learning style theories require teachers to adapt the flow of their courses according to the actual evolution of the learning process. For e-learning this is not a trivial task; it needs the development of the content in several versions (with different quantities of knowledge, at different levels of difficulty, with various examples) and requires the precise identification of the current status (type and level of expertise) of the user. While the first requirement implies several curricula segmentation and aggregation – several systems have implemented this scenario, the later needs a continuous and accurate classification of the observed user – a more difficult task, addressed by only a few systems.

In a review made by Papanikolaou and Grigoriadou [16], the researchers' effort to design adaptive e-learning systems are grouped in the following directions: providing adaptive presentation and curriculum sequencing, adaptive navigation support and adaptive collaboration support.

Regarding learning style measurement, there are several strategies for detecting and identifying styles [2], [3], and [8]. Based on monitoring user behavior, the automatic mechanisms use genetic algorithms and data mining techniques to classify and identify students' learning styles.

Mitchel, Chen and Macredie [13] use the field independent (FI) versus field dependent (FD) learning style classification for designing hypermedia interfaces adapted to styles. They conclude that matching the content to style is not necessarily better than mismatching, and that a specific presentation of content may restrict users from doing what they prefer. Using a data mining technique, Lee et al. ([3]) classify users in FD/FI styles by calibrating the answers from the cognitive styles analysis with user behavior.

eTeacher [18] is an intelligent agent which automatically evaluates a learning style profile from the observations of student actions and the analysis of log files. Using Felder's and Silverman's conceptualization of learning styles, eTeacher provides specific actions to users with different learning styles. For a sensitive user, the agent recommends that the student solve more exercises or study more examples.

Because there are so many models of learning styles, it is difficult to trace the use of every model within the e-learning domain. However, the most examined learning style is the Witkin [19] Field Dependence concept. This model belongs to the fixed factor classification presented at the beginning of the chapter.

The majority of e-learning researchers adopt the fixed factor approach to learning styles because of the following advantages: it is easy to determine learning styles; there exist rules for fitting content to particular styles and the promise that if the matching method is used, the student-learning outcome will improve. Unfortunately this doesn't always happen, even though the fixed factors measured by tests are calibrated by comparing the user interaction with the system.

The advocates of dynamic learning strategies are fewer, because it is difficult to design a user model in which all the parameters are permanently changing over time. However, the advantages of this model are significant:

- It overcomes the limitation of labeling, and allows the user to develop a better learning style, thus producing better learning outcomes.
- In order to do so, the system might use both matching, if the student has a learning style that improves learning outcomes and mismatching when the important learning strategies are missing from the student profile.

The identification of the learning style based on fixed factors can be done using a pre-test; the literature provides sufficient information regarding the relationship between the answers provided by the user (translated into features) and learning styles. Therefore, this type of identification requires only a suitable classifier to learn the user type from the set of static features. On the other hand, capturing the dynamic behavior (i.e. identifying changes in the learning style) is a more complex task, requiring continuous monitoring of the factors which influence it (of which very few are covered by the literature).

3. Adaptive e-learning

Adaptive e-learning refers to educational systems which adapt the learning content and the user interface according to pedagogical and didactical aspects. Modritscher [14] defined four main approaches of adaptive e-learning: macro-adaptive, aptitude-treatment interaction, micro-adaptive interaction and constructivist-collaborative approaches. While the first three are restricted to the content and learning process itself, the last one integrates newer paradigms in terms of adaptation.

In the *macro-adaptive* e-learning approach, the selection of instructional alternatives is based on the user's learning goals, abilities and achievements in the curriculum structure. Although it is an adaptive model, it is restricted to a small number of particularities a user could exhibit. Moreover, the particularities of a user are predetermined, so no enhancement takes place during the learning process.

The *aptitude-treatment* interaction approach focuses on the adaptation of instructional procedures and strategies to specific user characteristics. Therefore, it is more suited for achieving optimal learning for an individual. Here we have to deal with learner control, which refers to supporting the learning process according to the different abilities a user might have, providing full or partial control over the style of instruction. It is based on pre-task measurements (corresponding to the fixed factors) to adapt the instructional model. The drawback here is that the control is limited to a set of coherent and traceable rules which link different learner and learning variables to different tasks and instructional strategies. The lack of sufficient such rules leads to almost the same results as in a non-adaptive system.

When diagnosing the user's specific learning needs during instruction and providing instructional prescriptions, we deal with the *micro-adaptive* approach. Here the adaptation is achieved through a series of on-task measurements (the dynamic learning strategy). Therefore, the model is comparable to one-to-one tutoring. The process is a prescriptive one, optimizing the interaction between the user and the task by automatically adapting the composition and sequencing instruction, according to the user's recent performance on previous tasks. Other important aspects of micro-adaptation are the response sensitivity and interactive communication.

In the *constructivist-collaborative* paradigm the user plays an active role in the learning process, constructing his/her knowledge through experience. This approach benefits from the system's intelligence, including mechanisms of knowledge representation, reasoning, and decision making.

Most adaptive e-learning systems try to take full benefit from the advantages some model offers. However, such systems inherit the limitations or drawbacks of the model.

4. A Model for an Adaptive e-Learning System

A general template of an intelligent tutoring system consists of by four components: domain knowledge, student knowledge, tutoring knowledge and communication knowledge [20].

Our proposed model is a combined method between the aptitude-treatment and the micro-adaptive model, enhanced with some features from the constructivist-collaborative approach. The initial evaluation of the user, by means of the pre-tests measures the user's fixed factors (i.e. characteristics that change very slow over time) and generates the first instructional strategy, based on the static features of the user. Subsequently, the on-task measurements performed define the dynamic features, which continuously feed the intelligent component with knowledge about the user. This represents the adaptive part of the model, the one that captures the evolution in the user's learning style. Therefore, the system is able to adapt to the user's current performance. The constructivist flavor of the system is provided by the different types of annotations the user might perform, together with the system-user interactions. These elements are captured as dynamic features as well, contributing in the end to the continuous system adaptation to the user.

The learning process is strongly dependent on both the learning materials (difficulty, quantity, layout, requirement of prior knowledge) and the student's particularities (background knowledge, level of expertise, personal skills, type of learner). In a face-to-face education model, a student is able to take notes according to the information he/she considers necessary for a good understanding. Moreover, in an interactive class, the student is able to ask questions, request further explanations, ask for less/more difficult examples, for some background knowledge, the explanation of some concept, and so on. In a virtual environment on the other hand, the student has to search for each such piece of information by himself, either in the class, or, in case he/she cannot find it here, even further, on the internet. The later situation poses questions regarding the reliability of the information. Different adaptive e-learning systems provide these advantages in separate degrees.

Adaptive presentation refers to the content segmentation and management according to the student's particularities and goals, and is based on the identification of the user type. It is strongly related to curriculum sequencing. Adaptive navigation allows students to cover the curriculum in an individualized manner, according to their typology and preferences. Adaptive collaboration support consists of all the elements which bring the virtual learning system closer to a face-to-face learning environment.

The first action to take for attaining such objectives is the initial evaluation of the user for identifying his/her style and level of expertise. Based on those measurements, the content is presented according to the user's typology, providing an initial curriculum segmentation and adapted presentation. This task is error prone. Bias may be introduced by subjective elements (the mood of the user at the given moment might distort the answer to some questions, hence altering the classification), but also by some objective elements (as for instance regional irrelevance of questions in the test). Then, during the learning process, the user evaluation is continuously refined, through dynamic on-going measurements, in the attempt to better fit the learning strategy to the particular type.

The dynamic measurements capture the evolution of the user during the learning process and are ensured through different techniques, such as: quick notes measurement, navigation path assessment, evaluating the quality and the quantity of the conceptual maps, the quality of tests, and reassessment through the intelligent component.

The main interaction which appears in the learning process is based on the *quick notes* the user makes; they represent the virtual notes a user may take in the learning process, and revisit for review purposes. They allow the user to select a preferred content, to get more information on a particular topic, more examples, define own objectives, select relevant examples for understanding. The benefits of providing such a possibility are two-fold: first, the notes are projected into dynamic measurements (translated into features) that help for a better evaluation of the user profile, and thus for a better adaptation of the content presentation for that user. Moreover, all notes will be added to the user profile, hence, on further visits of the lesson this information is available (very similar to the notes taken in a face-to-face class); the process of revisiting personal notes is also captured and measured as dynamic features.

The identification of the *navigation path* is important for discovering the user's preference for a specific order of covering the content (such as depth first search versus breath first search), for a specific type of content (theory versus examples) or degree of difficulty (elementary notions versus difficult ones). The information captured here is also translated into dynamic features to better classify the user and further adapt the content.

Concept maps are graphical tools of knowledge representation and organization that allow the transfer of complex messages in a highly structured manner. Concepts are defined as a perceived regularity in events or objects, or records of events or objects. Propositions are "statements about some object or event in the universe, either naturally occurring or constructed. Propositions contain two or more concepts connected with other words to form a meaningful statement" [1]. Concept maps may be used in various ways: first, as knowledge representation, in a condensed and structured manner; secondly, concept maps may be used as evaluation tools, by automatic comparison between an expert and the user concept map; thirdly, concept maps are employed as learning activities – by activating knowledge learned in previous lessons, concept maps can be used during the introduction of a learning module, as a promoter mechanism of a specific cognitive activity (the recovery of information).

The *evaluation* of the acquired knowledge is a resourceful component for a learning environment. It allows the assessment to take place, which is a standalone objective. On the other hand, its overall result helps the judgment while classifying the user. Different evaluation components might trigger the categorization process of the user profile.

The *intelligent component* is designed for automatic adaptation of the content to the learning style, and resolves the issue of presenting the same quantity of knowledge, at the same degree of difficulty to all students. The learning styles can be identified statically, by the psychological test answers, or dynamically, by observing the user-system interaction. The best results are obtained by combining these methods.

The intelligent component is the part of the system which translates the answers to the initial test into static features, the interaction with the system (such as navigation path, quick notes, evaluation process) into dynamic features, and interprets them in order to offer an accurate and continuous classification of the user type. Different machine learning techniques can prove to be effective means for obtaining this goal.

Once a user profile is identified, the content is presented according to the corresponding type. Based on the 4 main learning styles, and on the 3 degrees of expertise, a matrix of 12 profiles is defined, and each lesson has the content adapted for each such profile (i.e. each lesson comes in 12 different flavors). While advancing in the learning process, the user interacts with the system. As soon as a particular user is re-labeled as being of a different category, the content presentation changes in a transparent manner.

The *process coordinator* is a regulative support tool destined to assist students in planning, monitoring, and evaluating their investigative efforts, within a practical application, from a particular lesson. It assumes a practical approach after all the theoretical notions have already been attended by students. It can be used as a standalone system (as complementary laboratory for face-to-face classes) or it can be integrated in the adaptive e-learning system.

An adaptive e-learning system may contain the above mentioned components. Although some of them could be valuable as standalone modules as well, their strength comes from their ability to interact.

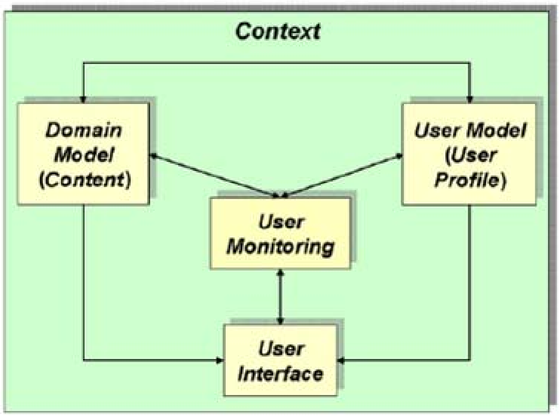

Figure 1. Conceptual architecture of an adaptive e-learning system proposed by Kritikou[10]

Conceptually, our proposed system extends the four-module e-learning architecture suggested by Kritikou [10] (figure 1). The domain model component stores information about the content to be presented to the user. The user interface is responsible for presenting content to the user in the most appropriate form. The user monitoring component and the user model ensure the continuous assessment of the user learning style. In our system, this task is accomplished by the intelligent module.

5. The Intelligent Module – Identifying the User Learning Style

In our first approach [4]for the intelligent component we have employed a Bayesian Network (BN). The initial test, measuring only the fixed factors (static features), contains 100 questions, with answers in a [1, 5] scale; the answers are recorded, and represent the original features. They have been further aggregated, according to domain (psycho-pedagogical) knowledge, resulting into 20 intermediate attributes (sub-scales). We have applied the test on a set of 304 first-year students in the technical field. Using the 20 predictor attributes, the BN model evaluated the percentage of membership of each individual to each of the four learning styles (I to IV). The membership of an individual to a class (learning style) has been determined by the largest percentage.

Although in general BN are robust and efficient classifiers, on our particular problem we have identified a flaw in the classification process: the outputs of the network have indicated very narrow separation boundaries between the four classes. For many instances, all four output percentages were close to the mean value (0.25), the membership to one class being biased. This raises the question of the correct identification of the class (learning style).

In a second approach [17], we have evaluated a clustering technique. We have performed several investigations with the k-means algorithm. We have focused on this method because of its advantages outweigh its drawbacks in this particular case (the number of clusters we wish to obtain is known a priori). Due to the unsatisfactory results obtained by our first approach, we have considered three different values for k (the number of clusters): 3, 4 and 5 – 4 clusters would reflect the theoretical taxonomy, while 3 or 5 clusters were evaluated as they might provide a better separation of the individuals, and thus help to combine two similar learning types or identify a new category of individuals respectively. According to the theoretical foundation, we expected that a 4 cluster typology will correctly identify the four learning styles. The results obtained with 4 clusters suggested that one of the clusters – containing all individuals with small scores, has no precise theoretical representation. Moreover, a 3 cluster grouping indicated a better performance in type identification, by collapsing the meaning directed and application directed types in a single one. To be noticed that they represent the good learning strategies. The discrepancies that we have observed between theory and the practical results obtained in the evaluation process can be attributed to two sources: (1) the cultural and regional differences between the population we have evaluated and the ones reported in literature and (2) the non-uniform distribution of the population currently evaluated (all the individuals were from the same year of study, same background and same learning objective).

To eliminate these shortcomings we have proposed, developed and evaluated a third method, based on a hybrid model, involving clustering and Self Organizing Maps (SOMs) [5], [6]. This new approach deals with both static and dynamic features of the user. To asses our new technique, we evaluated it on both synthetic and real data.

Figure 2 presents a block diagram of our new proposed user type identification component. It consists of two sub-components: a k-means clustering component and a SOM. The first is used for initial user type identification based on static attributes. Its results are used for initial SOM training and evaluation. The input of the SOM component has two parts: a static part (the static attributes, as recorded by the initial psychological test) and a dynamic part (the attributes identified during the user’s interaction with the system).

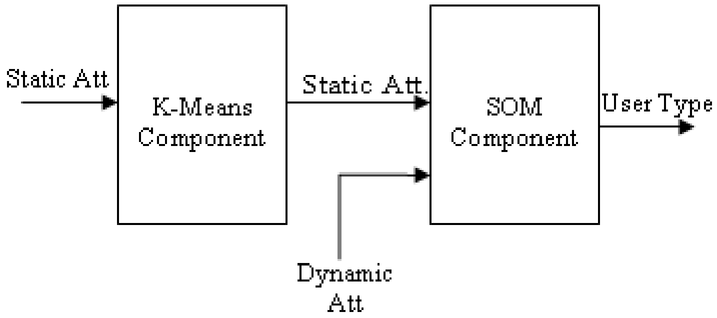

Figure 2. User type identification component

The values of the dynamic attributes may change over time, as the user learning style evolves; however, the static attributes are not re-assessed (the pre-test is presented to the user only once, during his/her first interaction with the system). The SOM component training process is continuous – the map configuration may adjust as the users interact with the system, and the values of their dynamic attributes change.

The SOM component is initially built using only the static attributes; all the dynamic attributes have their values set to zero. After this initial construction phase, the learning parameters of the SOM are set to low values in order to ensure that the model adjustments due to the dynamic features are made in time, representing a consistent user behavior. This is necessary because the user learning style cannot change abruptly and, therefore, a spike in the user's dynamic behavior must not produce major changes to the map topology. However, if the same behavior persists over time, it means that the user learning style has evolved and this will have an effect on the map topology and user classification. This desirable behavior is ensured through another mechanism: user history. The values of the dynamic attributes represent aggregates of the actual recorded values at different moments. More recent interactions weigh more, and the influence of past interactions is minimal, or absent. For this, a decay function is employed to aggregate the values of different user interactions with the system.

Over time, as the number of users being clustered mainly based on their dynamic attributes is increasing (since the static attributes don't change their values), the SOM component evolves and the influence of the dynamic attributes in the user type identification increases.

When a new user is introduced in the system, he / she has values only for the static attributes, so it will be first pre-clustered, using the values of these attributes. When the best-matching unit in the SOM is identified, the new instance will copy the values of the dynamic attributes from this node.

We have performed several evaluations of the component, on both real and synthetic data. The U-Matrix of the SOM on the real data samples representing the static attributes, suggests that users' typologies are not well defined (see figure 3). The lack of cluster separation can be explained by: (1) the non-uniform distribution of the learning styles over the population evaluated (all the individuals from the same domain – technical – so the meaning-directed learning style prevails), (2) the non-uniform distribution of the population evaluated (all the individuals from the same study year, therefore the same age segment).

To still achieve a validation of our method, we have performed a second series of evaluations on synthetic data, using two strategies for data generation: a Gaussian distribution, then a uniform one.

In the first approach, we have generated 1000 instances, 250 for each learning style, using a Gaussian distribution for each. The values of the attributes were in the interval [1, 5], with the mean 3.5 for the attributes that influence the respective user type and 2.5 for the others, and a standard deviation of 0.5. We have trained a Self-Organizing Map on these data samples. Figure 4 presents the resulted U-Matrix. As it can be observed, in the SOM model, the clusters representing the user learning styles are well defined. The results are in agreement with the learning style theory.

In the second strategy, we employed the same values as before, but for a uniform distribution. The results are presented in figure 5. We can observe that we obtain roughly the same models in both cases, with the four regions well separated. This means that, no matter what form of distribution appears in the data, as long as the learning styles are well represented in it, the SOM will provide a good separation of the types.

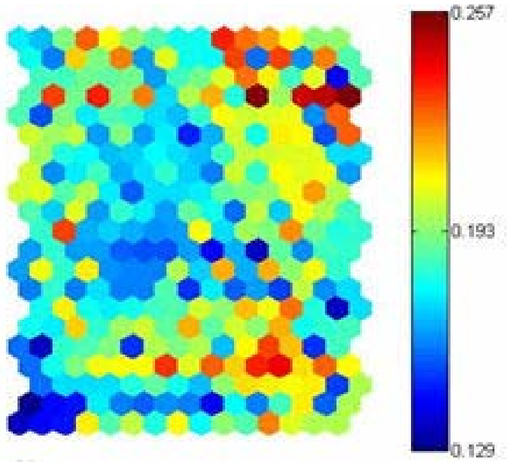

Figure 3. U-matrix of the SOM on real static data

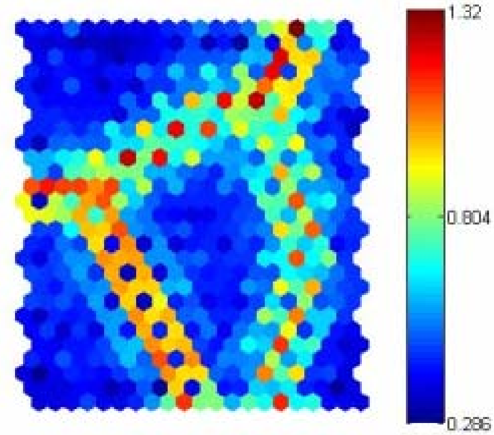

Figure 4. U-Matrix of the SOM, using synthetic data for the static attributes (Gauss)

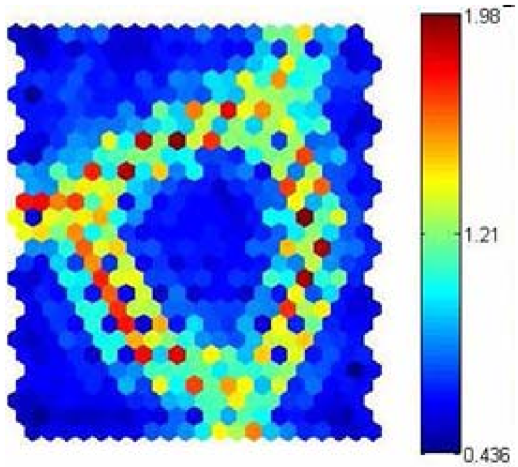

Figure 5. U-Matrix of the SOM, using synthetic data for the static attributes (uniform)

Starting from this model on static attributes we have integrated the dynamic attributes, representing the student interaction with the system, following the model presented in Figure 2. As the relation between dynamic attributes and learning styles is not clearly defined, studies in this field being relatively new, we selected five dynamic attributes: four from quick notes (definition, remember, I don’t understand, example) and the length of navigation path, all presented in section IV. Synthetic data was generated using a Gaussian distribution, based on our assumption on the dynamic attributes – learning styles relation; for the static attributes we used the previous generated samples. Figure 6 presents the U-Matrix of the SOM using both 20 static and 5 dynamic attributes. Comparing the U-matrices in figures 4 and 6, a better separation of the clusters can be identified in the last map. In the SOM corresponding to the dynamic and static attributes, it can be observed that one of the clusters - corresponding to undirected learning style - is not so well separated. This style is defined as being a combination of the other styles, representing the individuals that have not a clear learning style. Based on this observation it can be concluded that this SOM correctly identifies the user learning style using both dynamic and static attributes.

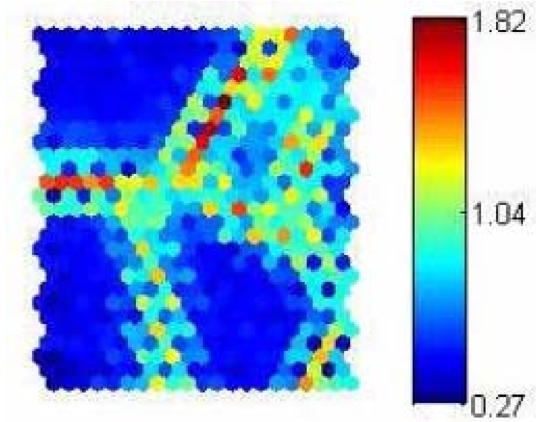

Figure 6. U-Matrix of the SOM, using synthetic data for the dynamic and static attributes (Gauss)

Our current efforts focus on identifying the most appropriate SOM metric to assess performance for our specific problem of user type identification and validating the proposed integration strategy using various scenarios and a partition-based approach for the SOM component. The most significant benefit of such an approach is the possibility to design each model independently.

6. Concept Maps – Instruments for Content Delivery and Automated Evaluation

Concept Maps (CM) are tools for graphical representation of knowledge in a highly structured manner. They are essentially DAGs (Directed Acyclic Graphs), with concepts in nodes and relations on edges. The main ways CM can be used are for knowledge representation, (re)organizing and grouping of information, and for evaluation.

When used for *knowledge representation*, a map consists of all the information needed to understand a concept and its relationships with other related concepts. As CM can be interconnected, a node could link to other maps, either at a lower level (representing background knowledge), or at an upper level (either to a more conceptualized scheme, or to more complex concepts). Thus, meta-maps are created. In this scenario CM are used during the learning process; they are valuable for making connections between different concepts, and in the review process.

CM represent also a valuable *instrument for evaluation*. Thus, knowledge could be assessed via automated comparison between the standard map (built by the expert – the tutor) and the evaluated map (built by the student). The degree of similarity estimates the quality of the answers. We have designed, implemented and evaluated a strategy for automated map comparison [12].

For the graph matching problem, we have investigated several techniques: an iterative matching [9], which is time efficient method, with satisfactory results; Gale and Shapley's algorithm [7] for stable marriage problem, which ensures the optimal match but is restricted for the case in which all nodes (concepts) are present in the map evaluated; and the hungarian algorithm [11], which finds also the optimal solution, relaxing the constraint of identical number of nodes in the two graphs compared.

For the evaluation, we have defined our metrics: starting from the number of nodes, denoted by c, and the number of edges, denoted by r, we have associated at the moment of building the expert map weights to each concept and relation, wc_i, i = 1 to c and wr_j, j = 1 to r, respectively (by default, wc_i= 50/c, and wr_j= 50/r), with $\sum wc_i + \sum wr_j = 100$. In the evaluation process, a correctly identified concept or relation corresponds to attributing the corresponding weight to the map under evaluation, with $tc_i \in [0, 1]$, $tr_j \in [0, 1]$, 1 being the result of a perfect match. The overall map matching, in case no false concepts and/or relations are added, will be provided by the score:

$$\sum tc_i * wc_i + \sum tr_j * wr_j,$$

while in case false concepts and/or relations are added, by:

$$\sum tc_i * wc_i - fc * p/c + \sum tr_j * wr_{ij} - fr*(100-p)/r$$

where fc is the number of false introduced concepts, and fr the number of false introduced relations.

In case not only perfect match is to be quantified (a more accurate evaluation of CM), a distance between concepts and relations is defined (dc_i and dr_j respectively). In this case, the mapping error (for concepts and relations matched) is:

$$E_m = \sum wc_i * dc_i + \sum wr_j * dr_j$$

By adding also concepts and relations not considered in the mapping (either falsely introduced or missing), we have the weight:

$$E_n = \sum wcne_i + \sum wrne_j + \sum wcns_i + \sum wrns_j$$

which gives the total error :

$$E_t = E_m + E_n$$

Taking the sum of weights of the two graphs as total error (100%), we get:

$$S_p = \sum wce_i + \sum wre_j + \sum wcs_i + \sum wrs_j$$

The evaluation of matching for two maps is given by:

$$100 – 100 * (E_t/S_p)$$

For a better identification of correct concept and relation matching, we applied several language processing stages: a stop words removal and a stemming algorithm. The two preprocessing steps belong to the lexical approach of content match. While being time efficient, its efficacy is limited to the correct identification of the same term for each item. However, in real world there are a lot of ways of expressing the same thing. To consider this, a semantic approach has been employed. The solution considers the utilization of an on-line synonyms dictionary; however, considering user-defined synonyms dictionaries is possible. The later prevails over the former, as it is domain-specific, and thus could offer a more accurate solution.

For evaluation, at present we have tested 5 expert CM, each compared with 3 distinct user CM. In most of the cases our solution is better than, or at least with similar performance to Cmap [15].

In the following we present a discussion on some of the results obtained. Figures 7 and 8 present an expert and a user concept map, respectively, for tree traversal. This is an example in which the two maps differ very little, and for which the semantic approach enhances the matching process. Both matching algorithms (iterative and hungarian) yield a 97% score, better than the score obtained by the Cmap tool, which identified only the “preorder” and “postorder” concepts as matching (figure 9).

Figures 10 and 11 present an expert and a user concept map, respectively, for a physics lesson. The scores obtained by both the iterative matching and the hungarian algorithm are of 55% match between the two maps. This example shows a current limitation of the semantic analysis:

even if the two maps have essentially the same meaning, because the relations are inversed they are not mapped (even if a synonymy relation existed between „is a” and „breaks into”).

7. Conclusions and Future Work

We have presented our view on the adaptive e-learning strategy. We have designed, implemented and evaluated the model of an e-learning system containing elements from the aptitude-treatment strategy (via fixed factors measurements), the micro-adaptive approach (by measuring dynamic features via quick notes, navigation path and concept maps employment) and constructivist-collaborative approach (by means of the process coordinator). The most challenging task is represented by the intelligent module – the component that identifies the user's type. Our current solution consists of a layered approach: a clustering layer, for the initial assessment, based on the fixed factors (user's static features). The second layer consists of a SOM that receives both static and dynamic features. As the users’ interaction with the system intensifies, the structure of the SOM changes accordingly, indicating the current user type. The experiments on synthetic data have shown a correct identification of the four learning strategies mentioned in the literature. Moreover, they indicate an even better separation of the clusters by the evaluation of both static and dynamic features. This is a welcome validation of our assumption that dynamic attributes are better indicators of the evolution on the user learning style.

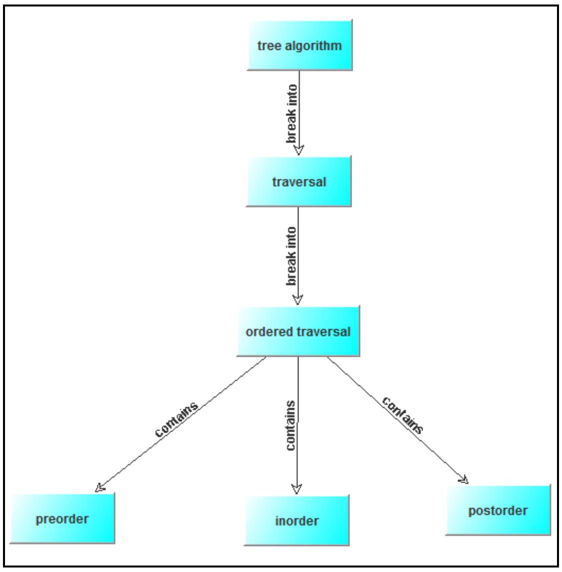

Figure 7. Expert concept map, tree traversal

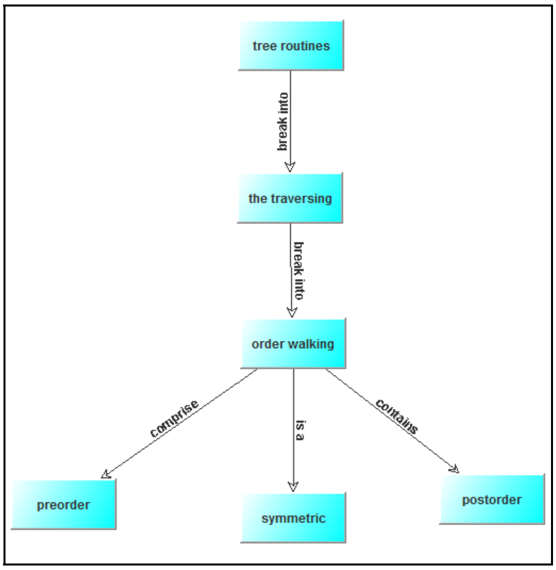

Figure 8. User concept map, tree traversal

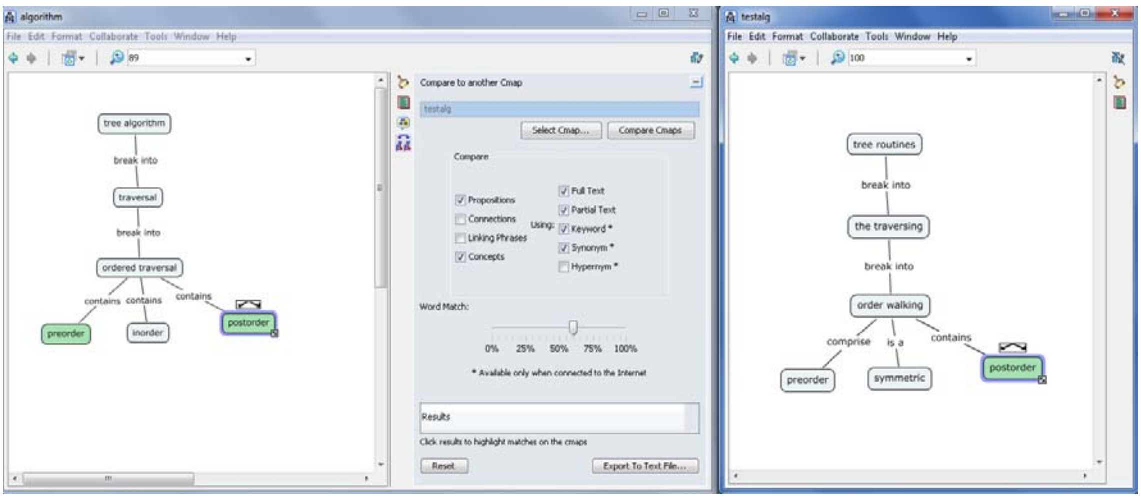

Figure 9. Cmap comparison of the expert and concept maps, tree traversal

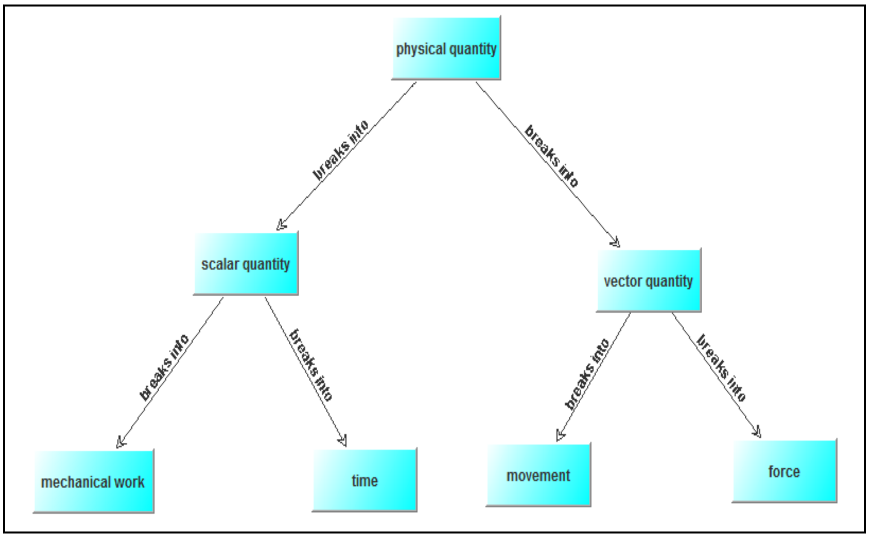

Figure 10. Expert concept map, physics lesson

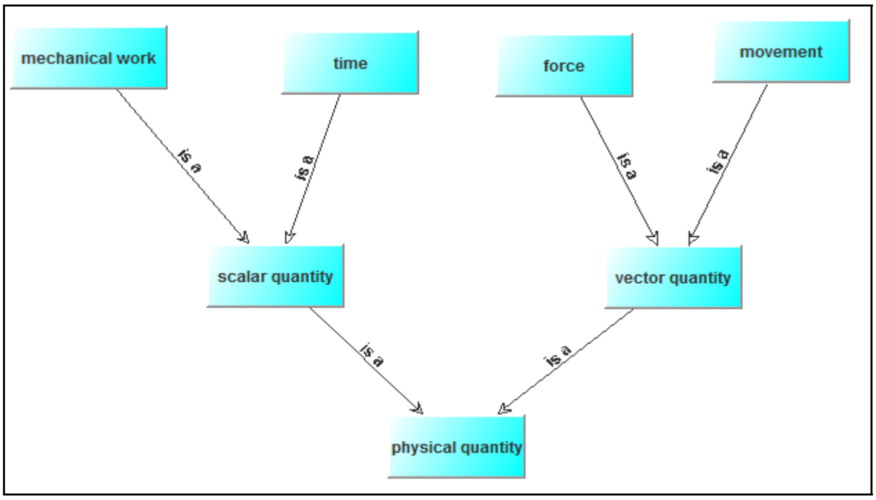

Figure 11. Student concept map, physics lesson

In terms of concept maps we have implemented a solution for automated CM evaluation: we proposed our own similarity evaluation, based on graph matching algorithms, and lexical and semantic content processing. The experiments performed so far showed that our solution is better in most cases than Cmap.

Our current interests focus on providing a thorough evaluation of our proposed model for user type identification, using various metrics, scenarios and a partition-based approach for the SOM, i.e. employ an identification-based strategy rather than a separation-based one. Thus, one SOM for each user learning style can be separately built and tuned, resulting in a more accurate model for each type.

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