International Journal of Inventive Engineering and Sciences (IJIES)
ISSN: 2319-9598, Volume-2 Issue-12, November 2014

Proposal for an Automatic Identification Model of Learning Styles

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Abstract— Hypermedia environments are becoming essential tools to enhance the educational value in teaching. This use is seen by facilitating the coming of the web world that offers us the opportunity to access hypermedia resources on the Web. The implementation of some educational activities in the form of hypermedia, can enhance the learning of cognitive skills in some learners. However, several LMS (Learning Management Systems) offer non-adapted to different types of learners learning activities. Now a Adaptive educational hypermedia system well designed, can generate varied and adapted to each profile educational activities. The consideration of values is very important to get to offer appropriate activities, and produce appropriate feedback. If this system called automatic identification of learning styles which is the subject of this document model, taking into account key factors such as learner preferences, values, characteristics and types of feedback, is to arrive interpret preferences peculiarities that distinguish each user. So we group a set of patterns each with its appropriate weight for each learner, through which one can determine the corresponding values of each characteristics in Learning Style Model. Once this is accomplished, we come to calculate the value of distinct preference for each profile, and the value of the confidence level based on the availability of data on each learner associated to each characteristic. To validate our model, which is still in experimental stage, we stage of implementation of the necessary tools. Once confirmation is made, the model will be used as an analytical tool.

Index Terms— Adaptive hypermedia system, learner model, learning styles.

I. INTRODUCTION

E-Learning is a very dynamic area, dominated by Learning Management Systems (LMS), which are integrated systems offering support for a wide range of activities, but do not provide personalized services. All learners have access to the same set of educational materials and resources, regardless of differences in learning style of each. Adaptive Educational hypermedia system, trying to offer an alternative to the non-individualized approach, offering a variety of services tailored to the learner profile. The question that arises is how to reliably determine the learning style of each learner? The objective of this work is to propose an automatic identification model of learning in order to collect a set of features styles, preferences and specify the value of each of these characteristics with a coefficient of reliability.

Manuscript Received on November 2014.

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II. LITERATURE REVIEW

A. Adaptive Hypermedia System

An adaptive hypermedia system is a hypermedia system which adapts autonomously [1]. It monitors the behavior of the learner, stores it in a user model and dynamically adapts the system to the current state of the user model. The system uses the actions of the browsing user's questionnaire responses and the initial information it can provide to adapt nodes and navigation. These adjustments can be made by changing predefined presentations by building. The goal of a hypermedia system is to make information easily accessible to the learner, and to improve the flexibility and comfort, a hypermedia system provides each user. This objective is achieved by gradually adapting the content and functionality at the level of competence and interest of the learner. The Dexter Reference Model [2] is used as the basis for this type of hypermedia. The hypermedia system consists of three layers, Run-Time layer, storage layer and component layer. To support adaptation, the storage layer consists of three models: the model domain, the user model and the model of adaptation.

B. Learning Style (LS)

Learning style is one of the individual differences that play an important role in learning. Learning style designates everything that is characteristic to an individual when she/he is learning, i.e. a specific manner of approaching a learning task, the learning strategies activated in order to fulfill the task. There have been given several definitions:

- "a predisposition on the part of some students to adopt a particular learning strategy regardless of the specific demands of the learning task" [3].
- "the composite of characteristic cognitive, affective, and psychological factors that serve as relatively stable indicators of how a learner perceives, interacts with, and responds to the learning environment." [4].
- "an individual's preferred approach to organizing and presenting information" [5].
- "the way in which learners perceive, process, store and recall attempts of learning" [6].
- "distinctive behaviors which serve as indicators of how a person learns from and adapts to his environment, and provide clues as to how a person's mind operates" [7].
- "a gestalt combining internal and external operations derived from the individual's neurobiology, personality and development, and reflected in learner behavior" [4].

As we can see, learning style has been attributed several connotations in the literature. Learning styles can be seen as applied cognitive styles, removed one more level from pure processing ability usually referring to learners' preferences on how they process information and not to actual ability, skill or processing tendency [8]. According to (Riding and Rayner, 1998), the key elements in an individual's personal psychology which are structured and organized by an individual's cognitive style are affect or feeling, behavior or doing, and cognition or knowing, and this psychological process is reflected in the way that the person builds a generalized approach to learning. The building up of a repertoire of learning strategies that combine with cognitive style, contribute to an individual's learning style (Papanikolaou et al., 2006). Therefore, learning styles are cognitive behavioral, emotional and physiological characteristics of individuals and serve as relatively stable indicators of how learners perceive, interact and respond in a learning environment (Keefe, 1979, p 4;. Translation free). The team Coffield (2004) identified 71 models of different learning style, which is divided into 13 major types:

1. Allinson and Hayes' Cognitive Style Index.
2. Apter's Motivational Style Profile.
3. Dunn and Dunn's model and instruments of learning styles.
4. Entwistle's Approaches and Study Skills Inventory for Students.
5. Gregorc's Mind Styles Model and Style Delineator.
6. Herrmann's Brain Dominance Instrument (HBDI). Honey and Mumford's.
7. Learning Styles Questionnaire.
8. Jackson's Learning Styles Profiler's Learning Style Inventory.
9. Kolb.
10. Myers-Briggs Type Indicator.
11. Riding's Cognitive Styles Analysis.
12. Sternberg Thinking Styles Inventory.
13. Vermunt's Inventory of Learning Styles's.

III. MODELING

A. Definition and Notation

Formally, let *L* be a learner and *Pref(L)* be a set of learning preferences characterizing Learner *L*. As part of our work:

Pref(L) = {p_visual, p_verbal, p_abstract, p_concrete, p_serial, p_holistic, p_activeExperimentation, p_reflectiveObservation, p_carefulDetails, p_notCarefulDetails, p_individual, p_team}

It should be noted that the preferred *Pref(L)* are grouped on several dimensions, each with two opposite directions:

Dim(LS) ={ p_visual / p_verbal, p_abstract / p_concrete, p_serial / p_holistic, p_activeExperimentation / p_reflectiveObservation, p_carefulDetails / p_notCarefulDetails, p_individual / p_team}.

Thus the learner can present only one of the two opposing preferences, e.g. if *p_visual* ∈ *Pref(L)* then *p_verbal* ∉ *Pref(L).*

In addition, the learner may an intensity level associated to each preference (i.e. preference mild, moderate or strong). Thus, for each dimension C/¬C ∈ *Dim(LS)* can have $Val_{C/\neg C} \in \{-3,-2,-1,1,2,3\}$, where the values positive means a preference for axis C and negative values imply preference towards the axis ¬C with greater of absolute value, more intense preference (i.e. ±3 represents a strong preference, ±2 represents moderate preference and ±1 represents a lightweight preference). Preferences of each learner can be represented as a set of tuples (Dimension, value):

$PS(L) = \{(Dim_i\ Val_i),$ *where* $Dim_i \in Dim(L)$ *and* $Val_i \in \{-3,-2,-1,1,2,3\}\}.$

B. Association of the Relevant Reasons for LS Dimensions

We encode the values that can be taken by the models into three categories: high (H), medium (M), low (L). Therefore, for each configuration we need to establish a mapping of the set of values that can be taken by the pattern to the set {M, M, L}. One way to specify this mapping is using thresholds L↔M and M↔H. Some common values for these thresholds, based on the recommendations of the literature (Graf, 2007;. Garcia et al, 2007; Rovai and Barnum, 2003). It should be noted that the values of these thresholds depend to some extent on the structure and object of the training. However, the teacher must be able to change these values to suit the peculiarities of its course. We can now associate values specifications with of LS Model (LSM) as are indicative. Since the characteristics of the LSM come in opposite pairs, whether a value of H for a pattern P may be associated with a characteristic C, when a value of L of pattern P can be associated with characteristic ¬C (for all dimensions C / ¬C ∈ Dim(LS). In addition, for each pattern, we can associate a weight, indicating the relevance (level of influence) it has on the identification of a learning preference. The weight of each pattern is noted hW (high weight), mW (middle weight) and lW (low weight). The values for the pattern are derived from learners measurements recorded by the system. Obviously, the higher the number of shares available is the reason many successful is more reliable. Therefore, we assign to each pattern a reliability coefficient, which is calculated from the number of corresponding shares in the system log. Thus, a pattern can have a high degree of reliability (hR), an moderate degree of reliability (mR) or a low degree of reliability (lR). accordingly, the specifics of the course are included in the weight of units, while the peculiarities of learner interaction with the system are taken into account in the reliability values patterns.

C. The Calculation of the Preference of the Learner

For each feature C∈ LSM, we define a set of relevant patterns $P_1, P_2, \ldots P_n$, with weight $W_1, W_2, \ldots W_n$, $P_i \in \{H, M, L\}$, $W_i \in \{hW, mW, lW\}$. Each learner can determine the corresponding values all grounds for each characteristics in LSM., We can now calculating the value of preference for learning j with respect to the characteristic C with the following formula:

$$V_j(C) = \frac{\sum_{i=1}^{n} p_i^j R_i^j W_i}{n}$$

with $$p_i^j = \begin{cases} 1 \; si \; P_i^j = P_i \\ 0 \; si \; P_i^j = M \\ -1 \; sinon \end{cases}$$

The value obtained for $V_i(C)$ can be interpreted as follows: if $V_j(C) > 0$ then we can say that the learner j a preference for characteristic C if $V_j(C) < 0$, then we can say that learner j a preference for the reverse feature ¬C. In addition, the absolute value of $Vi(C)$ gives an indication of the strength of preference: a value close to 0 indicates a lightweight preference (a rather balanced learning style), while higher values imply stronger preferences. We can also calculate confidence value associated to each $V_j(C)$, which reflects the degree of confidence we can have value of preference for learner j feature C (based on Availability data for Learners j):

$$Confidence_j(C) = \frac{\sum_{i=1}^{n} R_i^j}{n}$$

Note that J confidence (C) ∈ [0,1]. Small value implies a low degree of confidence in the value Vj (C), while a large value implies a high degree of confidence.

IV. CONCLUSION

A conclusion section is not required. Although a conclusion may review the main points of the paper, do not replicate the abstract as the conclusion. A conclusion might elaborate on the importance of the work or suggest applications and extensions. The proposal, when experimental validation method is implemented as an analytical tool, offering the following features:

- configure weight pattern;
- configure thresholds pattern;
- calculate the first pattern values;
- calculate values and degree of trust for preferences learners;
- calculate various statistics.

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