Web Course Self-Adaptation

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Abstract

This paper describes the methodology of an intelligent agent for building a self-adaptive course on the Web. An important task, therefore, is to combine adaptability with the learner-driven course in order to get a self-adaptive mechanism. For this, we have suggested a new structure for a web course. Based on this structure, we have suggested a new method to evaluate the granularity level of each segment on the course. This method evaluates the segment that a learner most prefers. To achieve this goal, we design and implement an agent called a confidence agent. Our experiment to evaluate our adaptation method shows that our approach greatly improves the domain model, and presents a course better related to the learner's needs.

1. Introduction

The large amount of information now available on the Web can play an important role in building a Cooperative Intelligent Distance Learning Environment (CIDLE). For this reason, we developed the Confidence Intelligent Tutoring System (CITS) to provide learners with a CIDLE as shown in Figure 1. The CITS employs a machine learning technique to predict the learners' preferred learning styles [1]. It infers their behaviors and adapts the presentation, based on their particular learning styles. In order to be adaptive and dynamic, the CITS searches the Web and returns documents related to a current concept of the discussion. Some parts of this information can be used to update the domain knowledge of the CITS. Although this abundance of information strengthens the course content, it can also overwhelm and confuses the learner. To overcome this shortcoming, when demonstrating a course, we give the learners some extra features built in the CITS by which they can modify the content of the course presentation.

In this paper, we have suggested a new structure for a web course. Based on this structure, we have proposed a new method to evaluate the granularity level of each segment of the course. That is based on a measure to evaluate the most likely segments a learner would prefer. An important task, therefore, is to design a self-adaptive agent that combines adaptability with learner-driven software. Adaptability means the system has some adaptable features [4].

The confidence agent is built, based on the CITS domain model (the granularity level of materials) and the user model (i.e. learning style, goals, etc.). So doing it adapts and presents a course better related to the learner's need.

This paper is organized as follows. Section 2 discusses the role of the confidence agent. In section 3, we present the role of the adaptation mechanism. We describe our approach to evaluate the granularity degree of the course segments, and discus the role of the adaptation algorithm. Section 4 presents the results of experiments conducted to test our methods. And section 5 concludes the paper.

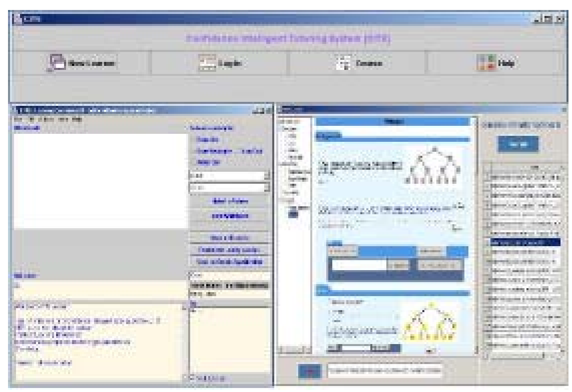

Figure 1 CITS User Interface

The next section illustrates the role of this confidence agent, and discusses how can the confidence agent achieves the objectives just mentioned.

2. The Roles of the Confidence Agent

The confidence agent works on the server side. Based on the granularity level of materials and the user model the agent can observe the learners' behaviors, allow them to insert and remove parts, and update the course materials. In fact, we need to define a way by which the confidence agent can keep track of learners, and construct the Web course that meets learners' needs. The framework of the confidence agent consists of three components:

- Keep track of learners on the current learning session.

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- Calculate the granularity degree of each segment in the course.
- Adapt the course to the behavior of learners and to specific learner needs.

Here is how the agent we developed adapts a course presentation (content). During a learning session, the confidence agent presents a concept to the learner structured as shown in Figure 2. This figure shows the presentation of the concept of a “heap” as part of a course on data structures. Each course consists of a header and 5 fragments (parts): background, definition, problems, examples, and exercises.

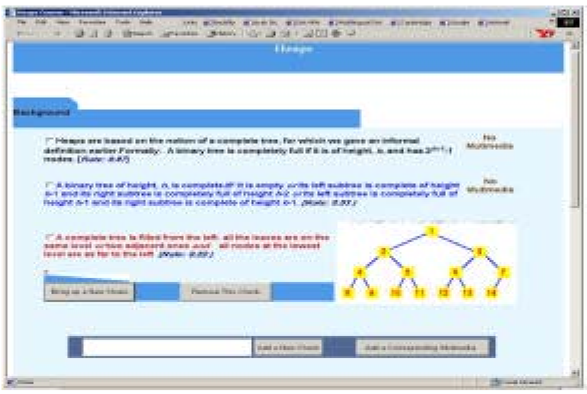

Figure 2 Example of course presentation

Each fragment contains different chunks of text grouped with a checkbox, images, and media. For each chunk there is a learner rating, which is used to measure the granularity of the chunk. The fragment includes three different colored chunks: black chunk represents built-in knowledge in the domain module. Blue chunk corresponds to pending knowledge; pending knowledge is Web extracted knowledge. There's still time to add it to the domain knowledge, though already it is marked as recommended by some learners. Red chunks correspond to knowledge that the CITS acquired through previous learning sessions from the Web. Each fragment contains a frame at the bottom that allows the learner to add a new chunk along with its corresponding multimedia file. Furthermore, the learner can bring up a new red chunk or erase any chunk he or she does not recommend.

3. The Role of the Adaptation

According to [8], the architecture of the Adaptive Hypermedia Application Model (AHAM) relies on three factors: a domain model, a user model, and an adaptation model. In the confidence agent, the user model represents the relationship between the user and the domain knowledge model. Our adaptation approach for the course takes into account the following roles: 1) the user model: learner’s goals, learning style, behaviors, and preferences. 2) the domain model: a granularity level of the course materials.

To perform adaptation based on the domain and user models, we need a standardized way to represent the course resources and to insert, remove, and exchange them, to specify how the system tracks the user’s browsing behavior.

3.1. Domain Knowledge Model

Adapting the course’s web page presentation is usually executed by managing text fragments [5]. Brusilovsky’s technique depends on conditionally showing, hiding, highlighting or dimming fragments on the page presented to learners.

The idea is to represent domain knowledge as a hierarchy of concepts. We use dominant meanings to define and join each concept. These dominant meanings consist of a set of meanings (concept names) that best describe a concept or that reflect the particular view of specific learners on the concept [1]. For example, a concept like “Queue” on a course data structure can be fitted by meanings such as, enqueue, dequeue, fifo, etc. In our approach, as shown in Figure 3, the course consists of some concepts. Each concept is composed of five fragments: background, definition, problems, examples, and exercises. For each fragment, there are links to three chunks that define it. Each chunk consists of atomic units, such as text, images, audio, and video.

Following the above structure we can represent a chunk Γ as follows: $\Gamma = \Gamma(T, I, A, V)$ where T, I, A, and V represent a numerical value of a granularity of the text, images, audio, and video of the chunk Γ respectively.

The following subsection explains how the confidence agent manages these chunks by using the suggested algorithm in order to adapt the course presentation.

3.2. Adaptation Algorithm

Our approach keeps track of evolving characteristics of the learner, such as chunks read, added and erased. These values are recorded in the user model and are used as one item for determining the granularity level of each chunk. The second item is to determine the dominant meaning probability between a chunk and the concept, which is taught [2].

Many researchers have used the granularity degree in the adaptation [4, 6, 7]. But the authors did not use a way to compute the granularity degree. In this paper, we suggest a method to calculate the granularity degree of each chunk involved in the Web course. In this paper, we suggest another way to compute the granularity rather than we used at [2]. Suppose that C_h is a concept that is slected to be taught in a learning session and $\Gamma = \Gamma(T, I, A, V)$ is an extracted chunk. And suppose also that a set of dominant meanings of the concept C_h is $\{w_1, ..., w_m\}$.

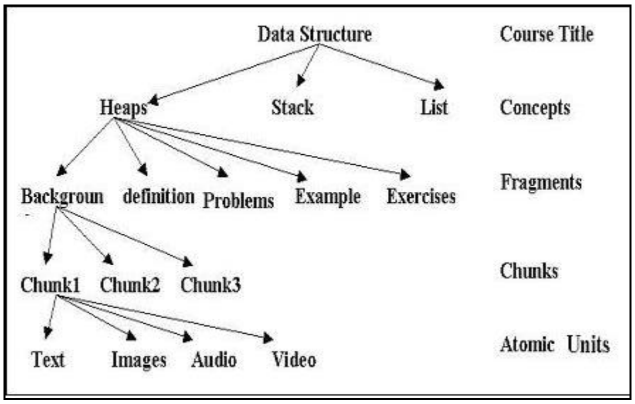

Figure 3: part of a concept hierarchy of the domain knowledge

In our proposed approach, each concept consists of some dominant meanings. We claim that the more a chunk consists of a session's dominant meanings, the more closely a chunk will be related to its concept [1]. Based on these, we compute the distance space between the chunk Γ (i.e the text T of the chunk Γ) and the concept C_h. Suppose that a word w_{ch} symbolizes the concept C_h.

Then, the distance can be evaluated as follows:

$$P(\Gamma \mid C_h) = \frac{1}{m}\left[\sum_{j=1}^{j=m} \frac{F(\Gamma \mid w_j)}{F(\Gamma \mid w_{ch})}\right] \quad (1)$$

Where the functions $F(\Gamma \mid w_j)$ and $F(\Gamma \mid w_{ch})$ represent the frequency of occurrence of the two words w_j and w_{ch} in the chunk Γ.

To evaluate the particular view of specific learners on the chunk Γ, we define a new function that depends on the user model. Suppose that the number of times the text, images, audio, and video of the chunk Γ are erased is E_T, E_I, E_A, and E_V respectively. The number of times the concept C_h is visited is C. We consider that a chunk that is not erased by the user is read and recommended. Then we can calculate the importance value of the chunk Γ for the concept C_h as follows:

$$E = E_T + E_I + E_A + E_V \quad (2)$$

$$I(\Gamma \mid C_h) = \frac{C - E}{C} \quad (3)$$

Finally, from formulas (1) and (3), we can evaluate the granularity level $G(\Gamma \mid C_h)$ of the chunk Γ for the concept C_h as follows::

$$G(\Gamma \mid C_h) = P(\Gamma \mid C_h) + I(\Gamma \mid C_h) \quad (4)$$

One of the major challenges of adaptation is to determine which chunks should be presented to a particular learner. The adaptability of the confidence agent depends on the effective use of the granularity level of each chunk. The adaptation algorithm is designed to return a top chunk that meets learners' needs. For that, we design a recommendation algorithm, which return a sorted set of suitable chunks for the set $\{\Gamma_1, ..., \Gamma_n\}$ related to the concept C_h:

Recommend Algorithm [Chunks Set $\{\Gamma_1, ..., \Gamma_n\}$, Concept C_h]

1. Compute $G(\Gamma_i \mid C_h) \quad \forall \Gamma_i, i = 1, ..., n$
2. Sort $\{\Gamma_1, ..., \Gamma_n\}$ related to the corresponding value of $G(\Gamma_i \mid C_h)$ in decreasing order.
3. Return the sorted set of suitable chunks $\{\Gamma_1^s, ..., \Gamma_n^s\}$

The adaptation algorithm based on the role of adaptation mentioned above can select the top chunk from the set $\{\Gamma_1^s, ..., \Gamma_n^s\}$ that meets the learner needs.

Adaptation Algorithm [Chunks Set $\{\Gamma_1, ..., \Gamma_n\}$, Concept C_h ,Learner's learning style L]

- Recommend Algorithm $[\{\Gamma_1, ..., \Gamma_n\}, C_h] = \{\Gamma_1^s, ..., \Gamma_n^s\}$
- If L = *Visual style* then
  - Sort $\{\Gamma_1^s, ..., \Gamma_n^s\}$ related to the value of $(T + I + V)$ in decreasing order.
  - Return the chunk that corresponds the first value
- If L = *auditory style* then
  - Sort $\{\Gamma_1^s, ..., \Gamma_n^s\}$ related to the value of $(T + A)$ in decreasing order.

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- Return the chunk that corresponds the first value

- If L = *kinesthetic style* then
  - Sort $\{\Gamma_1^s, ..., \Gamma_n^s\}$ related to the value of ($T+V$) in decreasing order.
  - Return the chunk that corresponds the first value

- If L = *visual & auditory or visual & auditory & kinesthetic* then
  - Sort $\{\Gamma_1^s, ..., \Gamma_n^s\}$ related to the value of ($T+I+A+V$) in decreasing order.
  - Return the chunk that corresponds the first value.

The next section explains how we can represent course materials using XML.

4. Experiments and results

Our goal was to identify if the CITS with the confidence agent provided benefits over without the confidence agent. We conducted two experiments on a group of 10 learners. Table 1 shows the main features of this group, (the number of learners and their backgrounds), types of tutoring session and duration of experiment.

Table 1: Collection used for experiment

Number of learners in each experiment	*10*
Tutoring sessions of the first experiment	CITS without the confidence agent
Tutoring sessions of the second experiment	CITS with the confidence agent
Time period of the first experiment	1 week
Time period of the second experiment	1 week

The first experiment was dealt with the CITS without using the function of the confidence agent. The second was done with the function of the confidence agent. In the first experiment, learners were invited to discuss five concepts in a course on data structure. We provided roughly one week of training for each group. At the end, learners were asked to fill out questionnaires. The goal was to see whether the system provides good adaptation for a Web course, whether the chunks is represented correctly their concepts, and whether the adaptation meet their needs. On average, learners found that the proposed system provides a good adaptation for a Web course (8 on a scale of 1-to-10); that the chunks is represented correctly (slightly over 7 on a scale of 1-to-10); and that the confidence agent produces a sound adaptive course related to their needs (8 on a scale of 1-to-10).

In short, our experiment shows that this method can significantly improve domain model and provide a sound adaptation for a Web course.

5. Conclusions

This paper introduced the concept of a *confidence agent*, an agent designed to maintain course materials and adapt course presentation. We proposed a new representation for the domain model that allows the confidence agent to insert, remove and exchange course materials. Finally, we suggested a new method to evaluate the granularity of information that enables the agent to decide what information is presented to the learners.

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