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ملخص البحث بالعربية:
في الآونة الأخيرة، تزايدت الحاجة لإستخدام تقنيات الويب، وخاصةً في مجال التعليم، وهذا يفسر زيادة المحاولات لتطوير واقتراح الكثير من التقنيات الهدف منها المساعدة في دعم الطلبة أثناء العملية التعليمية. تطور التعليم الذكية (Intelligent tutoring systems) أحد تيارات البحث الحديثة، التي تحاول تقديم الإرشادات الفردية على أساس الحالة التعليمية للمتعلم. لتحقيق هذا الهدف، كثير من تقنيات وآليات التوجيه المعتمدة على فكرة التكيف أو الشخصية، تم إقتراحها. رغم ذلك، هذه التقنيات والطرق تتطلب الكثير من الجهد من قبل خبراء تصميم المعرفة. هذه الورقة تقترح نموذجا جديدا، يعتمد آلية دمج كل من خرائط المفاهيم (Concept Maps) و خرائط المعرفة الضبابية (Fuzzy Concept Maps). النموذج المقترح يجمع ميزات كلا النموذجين السابق ذكرهما. لمواجهة العملية التعليمية، تم اختيار تقنية الملاحة التكيفية كأداة لتوضيح فوائد النموذج المقترح. بناءً على ذلك، أجريت تجارب لتقديم أداء النموذج. نتائج الاختبارات أشارت إلى وجود فجوة في الأداء التعليمي لدى المجموعة التي تلقت النموذج المقترح، بناةً على ذلك، أجريت تجارب لتقديم أداء النموذج. النتائج أظهرت أن النموذج المقترح لتحديد النهج التعليمي أفضل من النموذج التقليدي.

Abstract
Web-based instructions have grown strongly, in particular, in the education, and this explained the huge attempts for development various approaches to help and support learners during their learning process. The web-based intelligent tutoring systems are becoming mainstream area of research and development that attempts to offer individualized instructions based on learner’s educational status. To pursue such goal, many powerful personalized/adaptive guidance mechanisms have been proposed. However, using such methods/techniques for providing learning suggestions requires a great effort from the side of domain expert. Thus, this paper proposes a new model which combines both the concept maps and fuzzy cognitive maps. The proposed model takes the advantages of both mentioned maps. To provide learning suggestions, the adaptive navigation technique is selected as tool to illustrate the benefits of the proposed model. An experiment was conducted to evaluate performance of our approach. By analyzing the results of the experimental and control groups, it was found that the learning performance of the learners who received learning suggestions by applying the proposed approach was significantly better than those who did not receive them.
I– Introduction

Providing learning suggestions is essential task in any web-based tutoring system and this explained the existing many powerful personalized/adaptive guidance mechanisms. Such mechanism aims to help and support the learners during their learning process or to advise them on what to learn. Notable example is the web-based intelligent tutoring system. By definition, web-based intelligent tutoring systems are web-based instructional systems that attempt to gather information about a learner’s learning status and then use this information to adapt the instruction to fit the learner’s need (Brusilovsky et al., 1993), furthermore, these systems try to satisfy all needs of an individual learner, especially personalization and individualized instruction. According to Brusilovsky (1996), there is number of methods and techniques use to satisfy the mentioned above needs:

3. Adaptive Content Methods: Additional explanations, Prerequisite explanations, Comparative explanations, Variants and Sorting.
4. Adaptive Navigation Methods: Global guidance support, Local guidance support, Global orientation support and Local orientation support.

However, using such methods/techniques for providing learning suggestions requires a great effort from the side of domain expert. Thus, in this paper, an innovative method that takes advantages of the concept maps and the fuzzy cognitive maps to guide learners through learning materials. The rest of this paper is organized as follows: Section 2 briefly reviews the backgrounds of the research. The proposed model is presented in Section 3. The evaluation results are presented in Section 4. Finally, the conclusions and future works are presented in Section 5.

II- Background

A– Architecture of a web-based educational system

There is no standard architecture for web-based educational systems (WESs). However, if we look closely at them we see that they show strong similarities in structures and functionality. In the core of WESs, the storage layer is a common layer. In WESs, this layer consists of three functionally different parts: The domain model contains a conceptual representation of the application domain. The user model contains a conceptual representation of all aspects of the user which is relevant for the adaptive hypermedia application. This includes an overlay model of the...
domain, but also the user’s background, experience, preferences or anything else that contributes towards the adaptation. The adaptation model describes how an event, such as the user following a link, results in a presentation, by combining elements from the domain model and the user model (see Figure 1). At the top there is the run-time layer which represents the user-interface and way of presentations (presentation specifications). At the bottom the within-component layer describes the internal, implementation-specific data objects. The (adaptive) hypermedia systems can access these objects using anchoring.

![Figure 1. The WESs model](image)

**B- Adaptive Navigation Support Techniques**

The research on adaptive navigation support can be traced back to the early 1990’s. At that time, several research teams had begun to explore various ways to adapt the behavior of hypertext and hypermedia systems to individual users (Brusilovsky, 2004; De La Passardiere & Dufresne, 1992; Kaplan et al., 1993). However, they shared the same core idea: adapt the presentation of links located on a hyperspace to the goals, knowledge, and other characteristics of an individual user.

Adaptive navigation support can guide the students both directly and indirectly and can work with larger amounts of learning material using simpler student models. The simplest technology of adaptive navigation support is direct guidance. Direct guidance suggests the “next best” node to visit according the user goals, knowledge, or/and other parameters represented in the user model. To provide direct guidance, a system usually presents an additional dynamic link (usually called “next” or “teach me”) which is connected to the “next best” node, as illustrated, in ISIS-Tutor (Brusilovsky & Pesin, 1994), SHIVA (Zeiliger, 1993), and Hyper Tutor (Pérez et al., 1995). Notable problem with direct guidance is that it does not support users who do not wish to follow the system’s suggestions. Thus, it should be used in conjunction with one of the “more supportive” technologies that are listed below:
1- Adaptive sorting technology is to order all the links of a particular page according to the user model and some user-valuable criteria: the closer to the top, the more relevant the link is. However, it can never be used with contextual links and maps; furthermore, it makes the order of links non-stable, thus, it is used for showing new links to the user in conjunction with link generation (Brusilovsky, 2004).

2- Adaptive hiding, removing and disabling technology is to restrict the navigation space by hiding, removing, or disabling links to irrelevant pages. Educational hypermedia systems (EHSs) were the main application area. In EHSs the adaptive hiding techniques were suggested and explored. However, several studies of link hiding demonstrated that this is a “unidirectional” technology and it is not recommended for learners who have sequential learning styles.

3- Adaptive annotation technology is to augment the links with some form of annotation, which tells the user more about the current state of the nodes behind the annotated links. These annotations are most often provided in the form of visual cues. This technology supports a stable order of links and avoids problems with incorrect mental maps. Annotation is generally a more powerful technology than hiding (hiding can distinguish only two states for the related nodes - relevant and non-relevant).

C- Concept Maps

Concept maps are tools for organizing and representing knowledge, where this representation takes the form of a graph or a diagram that shows the concepts and the connections among them (Novak, 1998; Geller, 2004). Figure 2 shows the key features of a concept map. Concept maps were originally designed as an education aid. This is because of theory underlying concept maps and models about how humans learn new things based on the old structure of knowledge. The main basic elements of concept maps are:

- **The concepts**: They are represented in the graph as the nodes which only appear once.
- **The links**: They join two related nodes. Furthermore, a node can be related to one or more nodes and arrow symbols are used to describe the direction of each relationship.
- **The propositions**: They are statements about object or event that indicate the type of relationships between these nodes.

The relationships between concepts can be static or dynamic dependent on the nature of domain model. We can at least distinguish three different types of static relationships (Caas et al., 2003; Jonassen, 2000):

- **Categorization**: When a concept $C_iC_iC_i$ is a subclass of another concept $C_jC_jC_j$.
- **Common membership**: When two concepts $C_iC_iC_i$ and $C_{i+1}C_{i+1}C_{i+1}$ are together a subclass of
another concept \( C_j \).

- **Intersection**: When a new concept \( C_j \) is generated by crossing two source concepts \( C_i \) and \( C_{i+1} \).

In dynamic relationships (dynamic relationships reflect the effect of a change in one concept on another), we distinguish two types of relationships:

- **Causality**: When a concept \( C_i \) causes another concept \( C_j \).
- **Correlation / probability**: When a concept \( C_i \) is directly or inversely related to another concept \( C_j \).

Concept maps are usually read from the top descending, thus, we will call them later “Hierarchical Concept Maps” (HCMs).

Figure 2: The key features of a concept maps

**D- Fuzzy Cognitive Maps**

Fuzzy Cognitive Map is a modeling methodology that used to representing causalities between objects of complex systems; Objects, in this graph, are used to describe main behavioral characteristics of the system and weighted arcs that connect objects to represent the causal relationships that exist among concepts (objects). Each concept is characterized by a number \( A_i \), that represents its value and it results from the transformation of the real value of the system’s variable, for which this concept stands, in the interval \([0, 1]\). Causality between concepts allows degrees of causality and not the usual binary logic (Kim & Lee, 1998), so the weights of the interconnections can range in the interval \([-1, 1]\). Figure 3 shows a simple Fuzzy Cognitive Map.

1- http://cmapskm.ihmc.us
Observing above graphical representation, it becomes clear which concept influences other concepts showing the interconnections between. Furthermore, the weights of the arcs between concept $C_i$ and concept $C_j$ could be positive ($W_{i,j} > 0$) which means that an increase in the value of concept $C_i$ leads to the increase of the value of concept $C_j$, and a decrease in the value of concept $C_i$ leads to the decrease of the value of concept $C_j$. Or there is negative causality ($W_{i,j} < 0$) which means that an increase in the value of concept $C_i$ leads to the decrease of the value of concept $C_j$ and vice versa. Or there is not relationship ($W_{i,j} = 0$).

The value in each concept is influenced by the values of the connected concepts with the appropriate weights. So the value $A^t_i$ for each concept $C_i$ is calculated by the following rule:

$$ A^{t+1}_i = f( k_1 \sum_{j=1}^{n} A^t_j W_{i,j} + k_2 \cdot A^t_i ) $$

$A^{t+1}_i$ is the activation level of concept $C_i$ at time $t+1$. $A^t_i$ is the activation level of concept $C_i$ at time $t$, $A^t_j W_{i,j}$ is the activation level of concept $C_j$ at time $t$, and $k_2W_{i,j}$ is the weight of the interconnection between $C_j$ and $C_i$. The coefficient $k_1$ and $k_2$ represent the proportion of the contribution of the previous value of the concept in the computation of the new value, the $k_1$, $k_2$ expresses the influence of the interconnected concepts in the configuration of the new value of the concept $A^t_i A^t_j A^t_k$ at time $t+1$ and $f$ is a threshold function.

### III- The Proposed Model

This section explains the proposed model that is used to guide learners during their interaction with the web-based educational systems. Thus, to pursue this goal, the following tasks need to solve:
1- How to represent domain model?
2- How does the proposed model select the next step? And how will it be represented?

To answer these questions, first, we propose to aggregate the concept maps and fuzzy cognitive maps in one map. We called such map “Fuzzy Sequential-Cognitive Map” (FSCM). In FSCM, the learning concepts are represented in the graph as nodes and labeled with two dynamic properties, namely: the understanding level of learner (LU) at time t and readiness degree R. The links represent the fuzzy causalities relationships (prerequisite relationships) that exist among concepts and degrees of influence. It must be mentioned that all values in the graph are fuzzy, so take values in the range between [0, 1].

![Fuzzy Sequential-Cognitive Maps: an illustrative example](image)

The adjacency matrix (weight matrix) of the proposed graph is calculated according to the proposed algorithm found in (Al-Sarem et al., 2011a).

\[
W = \begin{bmatrix}
0 & w_{12} & \cdots & w_{1n} \\
w_{21} & 0 & \cdots & w_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
w_{n1} & w_{n2} & \cdots & 0
\end{bmatrix}
\]

, where \(w_{ij}\) is the weight of the interconnection between \(C_i, C_j\) and \(w_{ij} \in [0,1]\), and the matrix diagonal is zero since it is assumed that no concept causes itself. The value of level of understanding altered according to the results of assessment. Thus, the domain model is complete with assessment concepts (questions) with relationships types “assessed by” as depicted in Figure 5.
One assessment concept is capable of assessing multiple learning concepts with different degrees of influence. Assuming that, the questions-concepts matrix is used to reflect that influence as follows:

\[
QC = \begin{bmatrix}
q_{c_1} & q_{c_2} & \cdots & q_{c_n} \\
q_{c_{n+1}} & q_{c_{n+2}} & \cdots & q_{c_{2n}} \\
\vdots & \vdots & \ddots & \vdots \\
q_{c_{m-1}} & q_{c_{m-2}} & \cdots & q_{c_{mn}}
\end{bmatrix}
\]

where \( q_{i,j} \) denotes the weighting or degree of relevance for each concept \( C_j \) to each question \( Q_i \) and \( 0 \leq q_{i,j} \leq 1 \). The value of level of understanding is calculated as follows:

\[
LU(C_i) = 1 - \frac{\sum_{j=1}^{n} (1 - g_{i,j}) \times q_{c_{i,j}}}{\sum_{j=1}^{n} q_{c_{i,j}}}
\]

where \( g_{i,j} \) represents the student’s answers for each question in the test sheet. If \( g_{i,j} = 1 \) then the student answers the question \( Q_i \) correctly, otherwise \( g_{i,j} = 0 \).

Example: let student’s answer vector be \( \overrightarrow{g_{ij}} = (1, 1, 1, 0, 1, 0, 1, 1, 0, 0) \) for \( m = 10 \) and QC matrix is as follows:
Then the understanding level of concepts:
\[
U(C_{i,t}) = LU(C_{i-1}) = 0.73, \quad U(C_{i}) = LU(C_{i}) = 0.70, \quad U(C_{i+1}) = LU(C_{i+1}) = 1, \quad U(C_{i+2}) = LU(C_{i+2}) = 0.08 \quad \text{and} \quad U(C_{i+3}) = 0.0.
\]
Referring to the second question, when the learner answers an assessment concept, its values of level of understanding lead to increasing the readiness value of the next connected concept that has not yet been studied. Thus, the readiness of concepts is altered according to the following equation:

\[
R_{i}^{t+1} = \frac{\sum_{j \neq i}^{N} LU_{j}^{t} \cdot W_{i,j}}{\sum_{j \neq i}^{N} W_{i,j}} \tag{3}
\]

where \( R_{i}^{t+1} \) is the readiness of concept \( C_{i} \) at time \( t+1 \), \( LU_{j}^{t} \) is the level of understanding of concept \( C_{j} \) at time \( t \) and \( W_{i,j} \) is the weight of the interconnection between \( C_{j} \) and \( C_{i} \). To select the next recommended concept, concept with maximum readiness value will be the candidate concept (recommended concept) for the next step.

\[
C_{\text{Next}}^{t} = \text{Max}(R_{i}^{t+1}) \tag{4}
\]

Armed with that, to tell the user more about the current state of the nodes, the annotation technology is used with five visual cues: the green color annotates that the concepts are understood, the red color annotates that the concepts are not-ready to study, the light blue color annotates
that the concepts are ready to study, the dark blue color annotates that the concept is strongly recommended to study first and white color annotates that the concept is not active.

Figure 6. A snapshot of the learning guidance process

IV- Evaluation
A- Experiment design
To evaluate the efficacy of the proposed approach, forty-four students, including fifteen females (31.82%) and thirty males (68.18%) were invited to participate in the computer-based Java course with fifteen concepts on the topic “Object Oriented Programming”. These students were divided into two groups, Non-supported group (control group) and Supported group (experimental group). The students in Non-supported group received the regular on-line course without learning guidance, while those in Supported group received the same on-line course, but with learning suggestions. All the students took a pre-test to evaluate if they had equivalent background knowledge and a post-test to evaluate their learning achievement.

B- Analysis of pre-test
As mentioned above, the aim of the pre-test is also to ensure that all students have the equivalent background knowledge required for taking the system.

The F-test: Tow-Sample for variances was applied to examine whether the variances across samples were equal. The result of this test was not significant which indicates that the difference between the variances was not significant ($p = 0.356 > 0.05$). Therefore, t-test: Tow-Sample Assuming Equal Variances was performed.
The result of t-test of the pre-test showed that there was no statistically significant difference between the mean scores for the two groups (\( t = 0.972 < 1.682, 2.018, p = 0.168 > 0.05 \)). Consequently, we concluded that the students in the groups had an equivalent level of knowledge.

C- Analysis of learning achievement (Analysis of post-test)

The post-test was conducted to compare the acquired knowledge between the two groups after receiving the learning suggestions. Similar to pre-test, the F-test: Tow-Sample for variances was applied to examine whether the variances across samples were equal. Figure 9 shows the result of this test.

Analysis of the test shows that the difference between the variances was not significant ($p = 0.140 > 0.05$). Therefore, t-test: Tow-Sample Assuming Equal Variances was performed.

From the mean value of the post-test (see Fig.10), the experimental group (Supported group) performed better than the control group. Since the value ($t = 2.590 > 1.682, p = 0.007 < 0.05$) which implies a significant difference between the performance of the groups. Therefore, we can conclude that the students who received the learning suggestions by our approach significantly improved their learning achievement compared to those in the control group.

V-Conclusion

This study proposes an innovative approach that based on the adaptive navigation support techniques to guide learners through learning materials. To present the domain model, we proposed to aggregate the concept maps and fuzzy cognitive maps in one graph that takes advantages of the both. In the proposed model, the learning concepts are represented as the nodes and labeled with two dynamic properties, namely, the understanding level of learner (LU) at time t and readiness.
degree R. The links represent the fuzzy causalities relationships (prerequisite relationships) that exist among concepts and influence degrees which are mind using the proposed algorithm in (Al-Sarem et al., 2011b).

To evaluate the efficacy of the novel approach, an on-line experiment was performed. The experimental results reveal that the students who received the learning suggestions by our approach significantly improved their learning achievement compared to those in the control group. Consequently, we conclude that the novel proposed model helps students to improve their learning progress, furthermore, can be used or integrated with the learning management systems (LMS).

References


