A Shortest Adaptive Learning Path in eLearning Systems: Mathematical View

Marwah Alian

Isra Private University, Amman, Jordan
marwah2001@yahoo.com

Abstract: The main challenge of e-learning systems is to provide courses tailored to different students with different learning rate and knowledge degree. Such systems must be also efficient, as well as adaptive. However, the most recent researches can be classified in to two major groups. The first group emphasizes the need for E-learning to be adaptive. While the second group, emphasizes the efficiency of such systems. In this research we set an objective to achieve both efficiency and adaptivity. This can be accomplished by selecting a representative algorithm for the first group and a representative algorithm for the second one, and attempting to combine them. This is justified by the fact that the first one aimed at improving the ability to select dynamically an appropriate learning object for a specific learner, while the second one aimed at selecting a learning path that costs least time and effort. In order to decide how these two approaches can be combined, the representative approaches were further analyzed, implemented and then experimented. As a result, a formalization and some modifications to these algorithms were suggested and a new approach is proposed. [Journal of American Science 2009;5(6):32-42]. (ISSN: 1545-1003).

Keywords: eLearning; Learning Object; optimized selection; shortest learning path.

1. Introduction

The term e-learning refers to online learning delivered over the World Wide Web via public internet or private intranet (Yu et. al., 2006). It is concerned with the computer based implementation of an educational system, thus it is a result of a computer oriented analysis and design of such system. Furthermore, web based education and training is a hot research area. Most of the progress made in this field has been influenced by the evolving technological infrastructure. However, the main challenge of the most recent research is to provide efficient and adaptive e-learning systems. To achieve efficiency, the e-learning systems are modeled as a directed graph where each node represents a Learning Object (LO) (Viet and Si, 2006). Each LO may contain one concept, one object, an image, or an audio session. Two nodes are connected if there exist a dependency relation, such that one node is a prerequisite to the other. Given a target node, the resulting graph can be used to determine the shortest path leading to such node. One of the most important features which has not been fully explored in this approach is the ability of the learning system to adapt to the learner’s profile (Yanwen and Zhonghong, 2004).

The e-learning systems act as an adaptive system if they select the path of learning that meet the student's requirements and needs and discard those paths, which are not in accordance with these needs. Furthermore, such an adaptive learning must be as efficient as possible (Andreev and Troyanova, 2006). To achieve such adaptivity and efficiency, two groups of solutions do exist. The first group emphasizes the need for e-learning to be adaptive (Atif et al., 2003; Karampiperis and Sampson, 2004; Liu and Greer, 2004; Viet and Si, 2006). The other group emphasizes the efficiency by selecting learning path which costs the least time and effort (Zhao and Wan, 2006) .

Based on these solutions the aim of our research is to select a representative algorithm from each group and combine these algorithms, in order to create a shortest path that is tailored for the learner's needs. Hence, the benefits of both groups are to be obtained.

This research is organized as follows; section 2 is a discussion of related work. Section 3 constitutes a formalization of the Eliminating and Optimized Selection (EOS) (Liu and Greer, 2004) and section 4 introduces a new approach that combines this algorithm with the shortest learning path algorithm with a respective modification of their different phases (elimination, selection and optimization). Experiment and results are given in section 5 and conclusion and discussion are given in section 6.

2. Related Work

Carchiolo et al.(2002) proposed an adaptive system for e-learning, which provides students with all paths from an initial knowledge to a desired one. The paths are retrieved and optimized based on student profile and teacher profile. Thus discarding those paths, which are not in accordance with the student's needs; the remaining paths are presented to the student to select one path and learn its course units.

Based on this system Zhao and Wan (2006) proposed an algorithm to select the shortest learning paths to learn the target knowledge. They assumed that a course is modeled as a graph, in which each node represents a knowledge unit (KU), and two nodes in the graph are connected if the first node is a perquisite to the later node. In addition, they considered the weight of the course graph to be managed by teachers. Then they defined the best learning path as the learning process that will cost the least time and effort. Thus, they introduced the shortest learning paths algorithm.

Atif et al. (2003) represented the content structure of the course by learning object graph (LOG), and classified the peaks of LOG into two categories: Mandatory learning object, and secondary learning object. Based on this structure, Viet and Si (2006) built an adaptive course generation (ACG) system to create adaptive courses for each learner based on evaluating demand, ability, background and learning style of them. In the course content there is a test in each section, an algorithm is proposed to select the learning objects (LO) from the learning object graph, which are suitable for the requirements of learner.

Karampiperis and Sampson (2004) addressed the learning object selection problem in intelligent learning systems and they introduced a decision model that mimics the way the instructional designer decides. They proposed a function that estimates the suitability of a learning object for a specific learner. The same methodology they proposed in educational hypermedia systems (Karampiperis and Sampson, 2004).

Karampiperis and Sampson (2005) suggested some changes on the previous methodology, such that they construct a similar function with several assumptions; the first one is that the elements of the user model defined by the designer and remain the same during the life cycle of the system. The second assumption is the learners characteristics and preferences stored in user model and the structure of the educational resource description model have been defined by the instructional designer. Then they used this suitability function for weighting the connections of the learning paths graph in adaptive educational hypermedia systems (AEHS). They assumed that using this function make the most suitable path is the shortest between two nodes, and they used simulation to compare the learning paths generated by the proposed methodology with ideal ones produced by a simulated perfect rule-based AEHS.

Liu and Greer (2004) proposed a framework for individualized learning object selection. This framework gives a suggestion to select a group of suitable learning objects for the learner, also it evaluates the suitability of a learning object using information about the learning object, information about learner, and historical information about the learner and the learning context. This framework was divided into three steps: eliminating irrelevant learning objects depending on some features of the learning object, the second step was to select learning object depending mainly on educational information and pedagogical principles, finally optimization for the selected learning objects had to be performed.

The analysis of the above-mentioned work reveals the fact that they can be classified in two major groups; the first group emphasizes the need for E-learning to be adaptive (Atif et al., 2003; Viet and Si, 2006; Karampiperis and Sampson, 2004; Liu and Greer, 2004). While the second group, emphasizes the efficiency (Zhao and Wan, 2006; Pythagoras and Demetrios, 2004)

As a representative for the first group we select the work suggested by Liu and Greer (2004); while a representative for the second one is the work suggested by Zhao and Wan (2006). This is justified by the fact that Eliminating and Optimized Selection (EOS) suggested by Liu and Greer (2004) aimed at improving the ability to select dynamically an appropriate learning object for a specific learner, while the shortest learning path suggested by Zhao and Wan (2006) aimed at selecting a learning path that costs least time and effort.

Our research aims at obtaining the benefits of both groups this can be achieved by an attempt to combine the above-mentioned representative algorithms. In order to decide how these two approaches can be combined, the above mentioned representative approaches were further analyzed, implemented and then experimented. As a result a formalization and some modifications to the above algorithms were suggested. Finally, a new approach is proposed to combine these representative algorithms.

3. Formalization of EOS

The key features of the EOS approach were to evaluate the suitability of a learning object in its situated context and to optimize the evaluation by using historical information about the learner, the learning object, and the learning context. The suitability of a learning object requires an evaluation based on its features. Whether a learning object is suitable depends on its own features and the context where it is used (Liu and Greer, 2004).

The analysis of this framework reveals the fact that the attributes of a learning object can be classified into two groups: eliminating attributes and selecting attributes, these attributes are used in different phases of EOS. The eliminating attributes are used in the filtering phase where certain Learning objects are eliminated if they do not match the learner's needs. The selecting attributes are used in the selection phase where each learning object assigned a value according to the comparison between the selecting attributes and learner's characteristics. The resulted set of learning objects will be candidate to enter the optimization phase, in which a value assigned to these learning objects according to the history of using learning objects by previous learners.

Table1: Learning Object attributes.

Attribute Name	Explanation
Learning Object ID	An Identifier of the learning object
Language ID	The language in which the content is presented
Environment ID	The technical requirements needed for presenting the learning object
Current learner ID	Current learner using the leaning object
Pedagogical Objective	The concept represented in the learning object
Cost	The price of the learning object
Expected Reading Level	The reading capability required by the learning object.
Prerequisite	The knowledge needed by the learning object
Typical Learning Time	Time needed for working with the learning object
Presentation Type	The way of presenting the content of the learning object

Table 2: Learner attributes.

Attribute Name	Explanation
Learner ID	An Identifier for the learner
Learner Name	First Name and last name of the learner
Learning objective	The subject or topic the current learner is going to learn
Learner Type	Learner's category
Background	Information about related knowledge or experiences of the learner
Knowledge in Related Area	Learner's level of domain related knowledge
Preferred Language	Language that the learner prefers
Reading Level	Learner's capability of understanding written materials
Listening Level	Learner's capability of understanding vocal materials
Reading Speed	Learner's speed of reading
Preferred Presentation Type	Learner's preference about the way in which the content is presented
Learning Style	Learner's way of learning new concepts or knowledge
General Academic Achievement	Information about the learner's academic performance
Environment ID	Computer environment (hardware, and software)
Financial Situation	Financial restriction
Time	Time the learner wishes to spend

Table 3: Learning Object History attributes.

Attribute Name	Explanation
Learner ID	Learner identifier
Learning Object ID	Learning object identifier
Accessing Time	The time when the learning object is accessed by the learner
Learner status	The learner status after using the learning object
Learning Style	Learner's way of learning new concepts or knowledge
Learner Type	Learner's category
General Academic Achievement	Information about the learner's academic performance
Interactions	Actions the learner makes while accessing the learning

	object
Evaluation	The learner's opinion about the learning object
Achievement	The assessment result of the learner after working with the object
Previous instructor ID	Teachers who have accessed the learning object
General Popularity	How often the learning object is selected for all type of learners
Specialized Popularity	How often the learning object is selected for certain type of learners

Table 4: Language attributes.

Attribute Name	Explanation
Language ID	The identifier of the language
Language Name	Human language name

Table 5: Environment attributes.

Attribute Name	Explanation
Environment ID	The identifier of the environment
Software	Operating system type in the environment
RAM	Memory exist in the environment
CPU	CPU type used in the environment

Based on learning object attributes a general framework to evaluate the suitability of a learning object is given in Figure 1. Where Eliminate (S) is a function that calculate the value $e_{eliminate}$ (0 or 1) for each LO_j in S, and then constructs the set S' as composing of learning objects with $e_{eliminate}$ equal (1). Select (S') is a function that assign a value e_{select} - considering selecting attributes- for each learning object in S', after that the function Optimize (S') is applied, in order to assign a value $e_{optimize}$ for each learning object in S'. Finally, the function Suitability (S') is applied to assign e_{final} for each LO in S', where e_{final} is the final evaluation result of the learning object and it is calculated as:

$$e_{final} = e_{eliminate} \times (e_{select} + e_{optimize}) \qquad (1)$$

The learning object that has the highest e final value is the most suitable learning object. In the following subsections we will discuss how to calculate each value of $e_{eminate}$, e_{select}, and $e_{optimize}$.

Let S = $\{LO_1,\ldots,LO_j\}$ the set of the learning objects from which an E-learning system is composed

$S_{eliminate}$ = Eliminate (S)

Where: Eliminate (S) constructs the sets $S_{eliminate}$ and S' such that:

- $S_{eliminate} = \{ e_{eliminate1}, \ldots, e_{eliminate\,j} \}$
- $e_{eliminate}$ is a value assigned for each $LO_j \in S$ as :

$$e_{eliminate\,j} = \prod^{i} a_{eliminate\,i}\ ,\ a_{eliminate} \in \{0,1\}$$

- $S' = \{ LO_j \in S \mid e_{eliminate\,j} = 1 \}$

S_{select} = Select (S')

Where: Select (S') constructs the set S_{select} such that:

- $S_{select} = \{ e_{select\,1}, \ldots, e_{select\,j} \}$
- e_{select} is a value assigned for each $LO_j \in S'$ as :

$$e_{select\,j} = \sum_i W_i \times a_{select\,i}\ ;\ W, a_{select} \in [0,1]$$

- W_i is calculated by formula (4)

$S_{optimize}$ = Optimize(S')

Where: Optimize(S') constructs the set $S_{optimize}$ such that:

- $S_{optimize} = \{ e_{optimize\,1}, \ldots, e_{optimize\,j} \}$
- $e_{optimize}$ is a value assigned for each $LO_j \in S'$ as:

$$e_{optimize\,j} = \sum_i W_i \times a_{optimize\,i}\ ;\ W,\ a_{optimizei} \in [0,1]$$

- W_i integer values to be given

$S_{suitability}$ = Suitability(S')

Where: Suitability (S') constructs the set $S_{suitability}$

- $S_{suitability} = \{ e_{final\,1}, \ldots, e_{final\,j} \}$
- $e_{final\,j}$ is a value assigned for each For each $LO_j \in S'$ as:

$$e_{final\,j} = e_{select\,j} + e_{optimize\,j}$$

Figure 1: Evaluation of the suitability of Learning Objects

3.1. Eliminating irrelevant objects

The first phase in EOS approach is eliminating irrelevant objects, in other words, filtering process. This step depends on some attributes such as the following attributes:

- Pedagogical objective (Keyword
- language
- Environment condition (software, hardware)
- Financial cost

The eliminating attributes are constraints so they are binary variables (1 or 0). If any attribute of the eliminating attributes did not match the requirements of the learner, the learning object will be omitted. In this step if an attribute satisfies the requirements, it has a value (1), and if the attribute does not fit in the current context, it has a value (0). Hence, the eliminating phase is based on applying the following formula for each learning object:

$$e_{eliminate} = \prod^{i} a_{eliminatei} \text{ where } a_{eliminate} \in \{0,1\} \qquad (2)$$

In Figure 2 we formalize a function that is used to calculate e eliminate for each learning object. This function is called Eliminate(S).

Let a_1, a_2, ……, a_8,be the following attributes respectively:

- Objective in Learner table
- Concept in Learning Object table.
- Financial Situation in Learner table
- Cost in Learning Object table
- Environment ID in Learner table
- Environment ID in Learning Object table
- Language ID in Learner table
- Language ID in Learning Object table

four eliminating criteria are computed as follows:

$a_{eliminate1} = (a_1 = a_2)$
$a_{eliminate2} = (a_3 \geq a_4)$
$a_{eliminate3} = (a_5 = a_6)$
$a_{eliminate4} = (a_7 = a_8)$

We define a function F1 that returns 1 or 0 as follows:

F1 ($a_{eliminate1}$, $a_{eliminate2}$, $a_{eliminate3}$, $a_{eliminate4}$)
If $a_{eliminate1}$ I $a_{eliminate2}$ I $a_{eliminate3}$ I $a_{eliminate4}$ then
return 1
Else
return 0

Figure2: Calculating of eliminating criteria $e_{eliminate}$

3.2. Selecting candidate learning object

To select the candidate learning objects. A suitability evaluation for each learning object is performed. This proceeds as follows:

- An importance analysis of the features surrounding each LO or context is performed. This analysis is reflected by assigning weight (W) for each attribute (feature) of the learning objects in a given context.
- A degree of match between these attributes and the requirement is performed. This degree is represented by a value between 0 and 1, and it is denoted by a_{select}

Thus, the selecting criteria for each LO is based on the following formula:

$$e_{select} = \sum W_i \times a_{selecti} \quad \text{where } W, a_{select} \in [0,1] \qquad (3)$$

For the purpose of implementation, we will use time, presentation type, and reading level as selecting attributes for the learning object. We will use the learner style as a context to determine the importance of these selecting attributes. For example, if the learner style was visual then the most importance LO attribute will be the time then the presentation type, and finally the expected reading level, but if the learner style was auditory then the attributes will be arranged according to their importance as follows: presentation style, time, and finally expected reading level. If the learner style was tactile and kinesthetic (i.e. learn by doing) then the most importance feature of the LO will be expected reading level, time, finally presentation style.

Hence, the importance of each attribute is presented by a weight W_i. According to the context, since in different context a learning object attribute affects the suitability in various ways. For the purpose of our implementation, the weight is calculated as follows:

$$W_i = P_i / N \qquad (4)$$

Where:
P : the preference degree of the selecting attribute (i) according to the learner.
N : the number of selecting attributes.

For instance, if the learner style was auditory then the weight for presentation style =1, weight for time =2/3, and finally weight for expected reading level =1/3.

The degree of match for each attribute is a value in the interval [0, 1]. Figure 3 shows a formal definition for calculating the degree of match for each selecting attribute.

Let the properties of a Learning Object defined as $a_1 \ldots. a_i$
Let the properties of a Learner defined as $a_1 \ldots. a_j$
Where $a_1 \ldots. a_i$, $a_1 \ldots. a_j$ are integer values
Let n be the number of selecting attributes
Then
$a_{select\ i}$ is defined as the degree of match for each selecting attribute for a learning object, where:

$$a_{select\ i} = \begin{cases} 0 , & \text{if } a_j < a_i \quad i,j=1 \ldots n \\ 1 , & \text{if } a_j = a_i \quad i,j=1 \ldots n \\ (a_i / a_j), & \text{if } a_j > a_i \quad i,j=1 \ldots n \end{cases}$$

Figure3: Calculating the degree of match a_{select}

3.3. Optimization phase

In some situations a learning object which match a learner's preferences might not be the best for the learner, so the selection of the most suitable learning object can be optimized based on:

- Previous usage of the learning object.
- Expert's evaluation.
- Similar learner's experience.
- Popularities of the learning object.

In Our implementation of optimization phase, we consider the following:

- General popularity of the learning object.
- Specialized popularity of the learning object.
- Previous similar learner's evaluation for the learning object.

Furthermore, the similarity between learners is based on learner style, learner level (e.g. beginner, expert… etc), and learner academic achievement. In order to select the learning objects that are suited for individualized learner, optimization phase is based on optimization criteria $e_{optimize}$ that can be calculated using the following formula:

$$e_{optimize} = \sum W_i \times a_{optimize\ i} \quad (5)$$

Figure 4 shows the calculation of $e_{optimize}$ for each learning object.

Let S'= { $LO_1, LO_2, \ldots LO_i$ } the set of selected learning objects
Let Av be the average of similar previous learners evaluation
Let L_{given} be the current learner using the system
Let L_{cls} be Learning Style for current learner
Let L_{pls} be Learning Style for previous learner
Let L_{ctl} be Learner Type for current learner
Let L_{ptl} be Learner Type for previous learner
Let L_{pev} be the previous learner evaluation for $LO_i \in S'$
Let G_p be General Popularity of $LO_i \in S'$
Let S_p be Specialized Popularity of $LO_i \in S'$
Let w_1, w_2 ,and w_3 be weights assigned for Av, G_p , and S_p , respectively.

For each $LO_i \in S'$
$a_{optimize1} = G_p$
$a_{optimize2} = S_p$
$a_{optimize3} = \text{average}(L_{pev})$

$$Av = \begin{cases} \text{average}(L_{pev}), \text{ if } (L_{cls} = L_{pls}) \ \mathrm{I} \ (L_{ctl} = L_{ptl}) \\ 0 \quad \text{, otherwise} \end{cases}$$

$e_{optimize\ i} = (w_1 \times a_{optimize\ 1}) + (w_2 \times a_{optimize\ 2}) + (w_3 \times a_{optimize\ 3})$

Figure 4: Calculating optimization criteria $e_{optimize}$

4. Discovering Suitable Learning Path

The result of merging the knowledge space(ontology plane) and the media space(content space) is a directed acyclic graph (DAG) of learning objects inheriting relations from both spaces, This graph contains all possible navigation paths that a learner can follow to reach his learning goal (Pythagoras and Demetrios, 2004). Thus, there is a need to optimize such navigation paths as well as to select the path that is most suitable for the learner. In order to achieve this, we suggest the following approach:

1. Given a DAG that represents all possible navigation paths, a sub graph that is relevant to a learner is constructed.
2. The sub graph is augmented with weights that represent the suitability of learning objects for the learner.
3. A shortest path algorithm is then applied to select an adaptive path that is as suitable and as shortest as possible for the learner.

The implementation of our approach is based on:

- EOS approach to calculate the suitability of learning object (Liu and Greer, 2004).
- A shortest path algorithm on weighted graph suggested by Zhao and Wan (2006)

However, since our approach is based on constructing a sub graph that is relative to the learner, the EOS approach has to be modified to take this into consideration. This is because the initial construction of the DAG will affect the subsequent phases and improve the overall optimization and adaptation.

4.1. Modifications on EOS approach

Our modification to the EOS approach is based on introducing relevance calculation. Such relevance calculation is needed to obtain the relevant sub graph. Thus the first phase of EOS is divided into two sub phases:

- Relevance calculation for the requested concept or objective. As a result, the most relevant learning objects will be candidate for the next sub phase.
- Eliminating irrelevant learning object according to the eliminating attributes (the language, the cost, and the environment condition)

Such a modification requires a corpus for the concepts and objectives that presented in the domain ontology. This facilitates the representation of the requested objectives, or concepts as terms of keywords within a domain.

For example, a specific concept in a specific domain, or an objective. Based on such terms a relevance value can be computed. For example, terms not frequent in the corpus have a low probability of being representative in the domain. Peñas et al. (2001) have define a formula that gives such a relevance value for the requested terms and we are going to use this formula with some adaptation.

Within the framework of our approach, the following information structures are added.

Two tables to represent corpus are needed; the first one consists of attributes that represent the concept and related information as shown in Table 6. While the other consists of the attributes that represent the concept objective corpus as shown in Table7.

Table 6: Concepts Domain Corpus attributes.

Attribute Name	Explanation
Concept ID	The identifier of the concept
Concept Name	Description of the concept
Domain	The domain in which the concept frequent
Frequency in Domain	Relative frequency of the concept in the specified domain

Table 7: Concept Objective Corpus attributes.

Attribute Name	Explanation
Concept ID	The identifier of the concept
Concept Name	Description of the concept
Objective	The objective in which the concept frequent
Frequency in Objective	Relative frequency of the concept in the specified objective.

Some attributes are added to the learning object table, such as Main Domain, Objective, and the attribute specialized popularity is separated into three attributes, Beginners Specialized Popularity, Trainers Specialized Popularity, and Experts Specialized Popularity as shown in Table 8.

Table 8: New Learning object attributes.

Attribute Name	Explanation
Learning Object ID	An Identifier of the learning object
Language ID	The language in which the content is presented
Environment ID	The technical requirements needed for presenting the learning object
Current learner ID	Current learner using the leaning object
Pedagogical Objective	The concept presented in the learning object
Cost	The price of the learning object
Expected Reading Level	The reading capability required by the learning object.
Prerequisite	The knowledge needed by the learning object
Typical Learning Time	Time needed for working with the learning object
Presentation Type	The way of representing the content of the learning object
Objective	The objective of the learning object
Main Domain	The domain to which the concept of this learning object belongs.
General Popularity	How often the learning object is selected for all types of learners
Beginners Specialized Popularity	How often the learning object is selected for beginners
Trainers Specialized Popularity	How often the learning object is selected for trainers
Experts Specialized Popularity	How often the learning object is selected for experts

- A relationship table is constructed to represents the relations between learning objects in the DAG as shown in Table 9.

Table 9: Relationship attributes.

Attribute Name	Explanation
Learning Object ID	An Identifier of the learning object
Related Learning Object ID	An Identifier of the related learning object
Relation Type	The relationship type between the connected learning objects

4.2. Constructing Relevant Sub Graph

Based on the DAG that represents all possible navigation paths and the above mentioned modifications as well as the newly introduced information (table 6, 7, 8, and 9), constructing the sub graph that is relevant to a learner proceeds as follows:

Firstly, a set of learning objects with relevance value denoted by $e_{relevane}$ for each learning object is constructed, where $0 \leq e_{relevane} \leq 1$. Then, the learning objects with zero value are eliminated. This can be formalized as follows:

Let $S = \{ LO_1, \ldots, LO_j \}$

$S' = Relevance(S)$

where: Relevance (S) is a function that constructs the sets $S_{relevance}$ and S', such that:

- $S_{relevance} = \{e_{relevance\ 1}, \ldots, e_{relevance\ j}\}$
- $S' = \{LO_j \in S \mid e_{relevane\ j} \neq 0\}$

where: $e_{relevance\ j}$ is a value assigned for each $LO_j \in S$

- $e_{relevance\ j} \in \{0, a_{relevance}\}$

where $a_{relevance}$ is calculated by the following formula:

$$a_{relevance}(c,dom,col) = 1 - \frac{1}{\log\left(2 + \frac{F_{c,dom} \times N}{F_{c,col}}\right)} \quad (6)$$

where:

$F_{c,dom}$: frequency of the requested concept in the specified domain or objective (dom)

$F_{c,col}$: frequency of the requested concept in the all collection .

N: the number of learning objects.

$e_{relevane}$ for a given LO is calculated by the function shown in Figure 5. This function is called by Relevance(S) for each LO$\in$S.

Let $a_1, a_2, \ldots, a_{10}$ be the following attributes respectively:
- Concept in Learner table
- Concept in Learning Object table.
- requested Objective or Domain in learner table
- Objective or Domain in Learning Object table
- Financial Situation in Learner table
- Cost in Learning Object table
- Environment ID in Learner table
- Environment ID in Learning Object table
- Language ID in Learner table
- Language ID in Learning Object table

Let a_{11} be the frequency of the requested concept in the specified domain or objective.
Let a_{12} be the frequency of the requested concept in all collection.
Let a_{13} be the number of learning objects in the system.

Five eliminating criteria are computed as follows:

$a_{eliminate1} = (a_1 = a_2)$
$a_{eliminate2} = (a_1 = a_2)$
$a_{eliminate3} = (a_5 \geq a_6)$
$a_{eliminate4} = (a_7 = a_8)$
$a_{eliminate5} = (a_9 = a_{10})$

Let $a_{relevance}$ be a relevance value of the requested term calculated as:
$a_{relevance} = 1 - (1 / \log_2((2 + (a_{11} \times a_{13})) / a_{12}))$

If $a_{eliminate1}$ I $a_{eliminate2}$ I $a_{eliminate3}$ I $a_{eliminate4}$ I $a_{eliminate5}$ then
  return $a_{relevance}$
Else
  return 0

Figure 5: A function to calculate $e_{relevane}$.

4.3. Sub Graph Weighting

DAG weighting is need to find the shortest path by any shortest path algorithm. Hence, the result of applying the shortest path algorithm is the learning path that covers the desired concepts objects, and reaches the learning goal by providing all information about cognitive characteristics and preferences for the learner. Such a weighting for the DAG is calculated by the following formula:

$$W = 1 - e_{final\,j} \quad (7)$$

e_{finalj} is calculated by a suitability function as shown in Figure 6, where:

- Select (S') is a function that assigns a value e_{select} -considering selecting attributes- for each LO in S', where e_{select} is calculated by formula (3).
- Optimize (S') is a function to assign a value $e_{optimize}$ for each learning object in S', where $e_{optimize}$ is calculated by formula (5).
- Suitability(S') is a function to assign e_{final} for each LO in S', where e_{final} is the final evaluation result of the learning object.

S_{select} = Select (S')
where: Select (S')is a function that constructs the set S_{select}
- $S_{select} = \{ e_{select\,1}, \ldots, e_{select\,j} \}$
- e_{select} is a value assigned for each $LO_j \in S'$ and calculated by the formula :

$$e_{select\,j} = \sum_i W_i \times a_{select\,i} \quad ; \quad W, a_{select} \in [0,1]$$

- W_i is calculated by formula (4)

$S_{optimize}$ = Optimize(S')
where: Optimize(S') constructs the set $S_{optimize}$, such that:
- $S_{optimize} = \{ e_{optimize\,1}, \ldots, e_{optimize\,j} \}$
- $e_{optimize}$ is a value assigned for each $LO_j \in S'$ as:

$$e_{optimize\,j} = \sum_i W_i \times a_{optimize\,i} \; ; W, a_{optimize\,i} \in [0,1]$$

- W_i integer values to be given

Then $S_{suitability}$ = Suitability(S')
where Suitability (S') constructs the set $S_{suitability}$ such that:
$S_{suitability} = \{ e_{final\,1}, \ldots, e_{final\,j} \}$
$e_{final\,j}$ is a value assigned for each $LO_j \in S'$ as:

$$e_{final\,j} = e_{relevane\,j} \times (e_{select\,j} + e_{optimize\,j})$$

Figure 6: A function calculates the suitability of a learning object

4.4. Selecting Adaptive path using shortest path algorithm

Based on the previous formalization and calculation of e_{final} as well as the fact that the learning object that has the highest e_{final} value is the most suitable learning object for a learner, The weights of the learning objects that are represented in the sub graph are calculated in away that is inversely proportional to their suitability value. Hence, the lower weight they have the more suitable they are.

5. Experiment and Results

Within the framework of this research, we have conducted several experiments as follows:

- Implementing EOS.
- Implementing the proposed approach.

Further experiments were conducted for testing and comparing EOS, and the proposed approach based on a number of created instances of learning object metadata, a number of learners, and simulated usage history of the learning objects.

The first experiment was conducted based on different learning objects that represent a concept that may appear in one domain or many domains.

The results of applying EOS and the proposed approach are given in Figure 7.

The obtained results show that the number of selected learning objects using the proposed approach is less than the number of selected learning objects using EOS. Also the number of selected learning objects using objective is not always greater than the number of the learning objects selected using main domain; this is because when a concept appears in one domain the objective will have less representative learning objects.

The second experiment was conducted based on concepts that appear in more than one domain and has more than one objective.

Table 10: The characteristics of the three LOs that were used for EOS experiment

Learning Object	Characteristics		
	Presentation Type	Time	Required reading Level
LO_1	Exercise	1 hour	Excellent
LO_2	Table	3 hours	Very Good
LO_3	Diagram	1 hour	Good

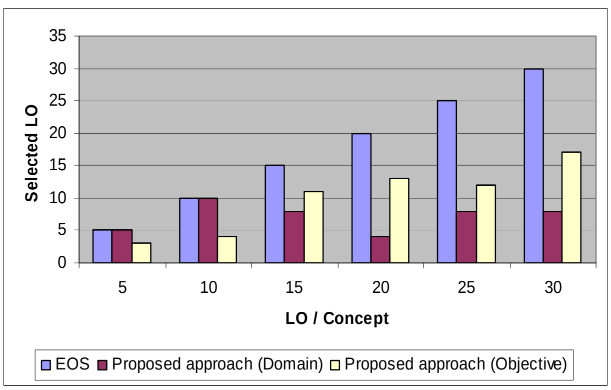

Figure 7: Selection results when a concept appears in one domain or more.

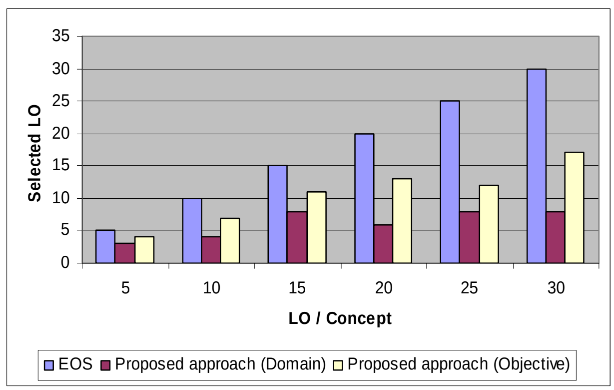

Figure 8: Selection results when concept appears in more than one domain.

The results are given in Figure8. These results show that the number of selected learning objects using objective always greater than the number of selected learning objects using a domain. This is because when a concept appears in more than one domain, each time it has the same objective but in different domains. Thus, when the selection depends on objective all learning objects that represents the specified objective for the requested concept will be retrieved, but in different domains.

The third experiment was conducted by applying the proposed approach to the same learners and learning objects that are used in the implementation of EOS, where EOS was experimented on three different learners and three learning objects (LO1, LO2, LO3), the characteristics of these learning objects are given in Table 10.

The first learner was a beginner with a very good reading level and had 12 hour for learning, his learning style was Visual and his preferred presentation type was videos. The second learner was a trainer with a good reading level, 5 hours to learn, his learning style is Auditory and his preferred presentation type was audios. Finally, the third learner was an expert with an excellent reading level, his learning style was Tactile & Kinesthetic (learn by doing), 20 hours for learning and he preferred slides as a presentation type.

The results are given in Figure 9. These results show how the suitability of the three learning objects varies from one learner to another.

The results show that the suitability variation using the proposed approach is more than in EOS approach, as shown in Figure10. This is because within the framework of the proposed approach the relevance calculation of a concept is added to the calculation of the suitability.

To evaluate the overall performance of the proposed approach, its selection results were compared to the selection results that obtained by experts. Such a selection was performed by both on the same simulated data set, which includes a number of created instances of learning object metadata, a number of learners, and simulated usage history of the learning objects. Such evaluation depends on the formula that was proposed by Karampiperis and Sampson (2005):

$$\text{Selection success}(\%) = 100 \times \frac{\text{Correct LO selected}}{m} \qquad (8)$$

where m is the number of requested learning objects from the media space per concept node.

The evaluation depends on the comparison between resulting selection sequence of learning objects by the proposed approach and the selection sequence produced by three experts with different points of view for preferences. Figure 11 shows the selection success for the resulting learning objects sequence while Figure 12 shows the average success for the selection of learning objects.

Both Figures show that the efficiency is affected by the number of desired learning objects (m). Hence, representing a concept by small number of learning objects is more efficient than large numbers of learning objects. However, the selection results of the proposed approach are competitive to the results obtained by the three experts.

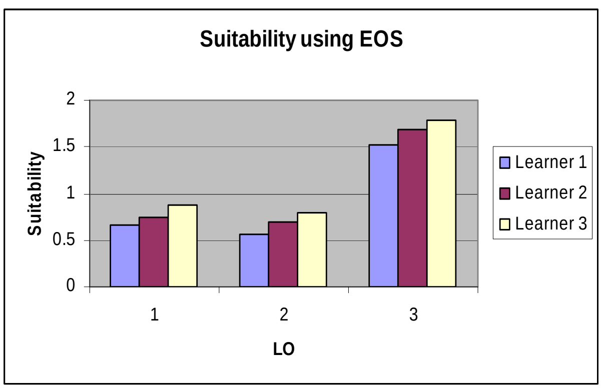

Figure 9: The suitability of three LO for three different learners

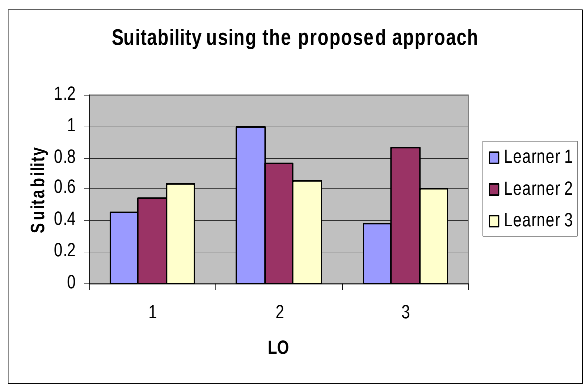

Figure 10: Suitability using the proposed approach.

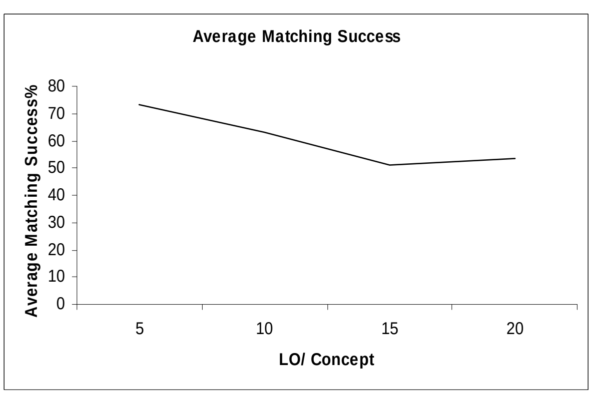

Figure 12: Average selection success using the proposed approach

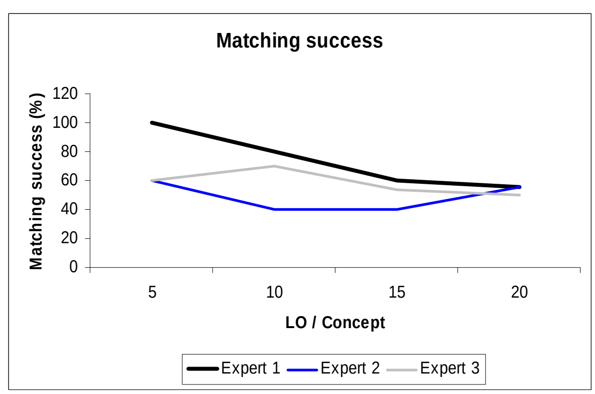

Figure 11: Selection success using the proposed approach

6. Conclusion

This research aims at improving the ability of selecting appropriate learning objects for a specific learner, as well as to select the shortest learning path for that learner. In order to achieve this we select two representative algorithms; Eliminating and Optimized Selection and the shortest learning path algorithm in order to obtain the benefits of both.

Based the DAG that represents all possible navigation paths between learning objects in an e-learning system, the first step of our approach is to construct a sub graph that is relevant to a learner. The second step is to augment the sub graph with weights that represent the suitability of learning objects for the learner. The third step is to apply a shortest path algorithm to select an adaptive path that is as suitable and as shortest as possible for the learner.

The augmented weights represent the suitability of learning objects. In order to calculate the suitability of a learning object, we have added some modifications to the EOS approach by a proposed framework that contains a suggestion on extending the learning object metadata specifications and selecting a short list of appropriate and relevant learning objects for the learner and the learning context. This selection is based on terms that represent objectives and concepts within a domain or more than one domain. This constitutes an improvements on EOS approach. This is because we have used an ontology based representation for LOs. This representation serves the learning objects selection and comparison much better. Furthermore the use of such terms instead of keywords ad full description is also a better approach. This motivated by the fact that the description is difficult to used for automatic learning objects comparison.

Our experiment showed that the improvement on EOS approach gives more specific and more optimized selection of learning objects that are suitable for the learner.

In addition, we have compared the produced LOs sequences selected by our proposed approach with that selected by different experts. Experiment results showed that the success in learning objects sequencing is affected by the number of learning objects that represents the desired concept and our approach is competitive with the results obtained by these experts. Finally, we have seen that the DAG construction affects the subsequent phases and improves the overall performance and adaptation.

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