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An adaptive navigation support system for conducting context-aware ubiquitous learning in museums

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ABSTRACT

In context-aware ubiquitous learning, students are guided to learn in the real world with personalized supports from the learning system. As the learning resources are realistic objects in the real world, certain physical constraints, such as the limitation of stream of people who visit the same learning object, the time for moving from one object to another, and the environmental parameters, need to be taken into account. Moreover, the values of these context-dependent parameters are likely to change swiftly during the learning process, which makes it a challenging and important issue to find a navigation support mechanism for suggesting learning paths for individual students in real time. In this paper, the navigation support problem for context-aware ubiquitous learning is formulated and two navigation support algorithms are proposed by taking learning efficacy and navigation efficiency into consideration. From the simulation results of learning in a butterfly museum setting, it is concluded that the innovative approach is helpful to the students to more effectively and efficiently utilize the learning resources and achieve better learning efficacy.

1. Introduction

In recent years, the innovation and advance of mobile computing and wireless communication technologies have led to a new research issue in education, that is, to develop a novel learning environment so that the students can learn in any place at any time (Sakamura & Koshizuka, 2005). Furthermore, with the help of sensor technology, the learning system is able to detect the learning behaviors of students in the real world, and hence more active and adaptive learning activities can be conducted. Such a learning scenario is called context-aware ubiquitous learning.

In a context-aware ubiquitous learning (u-learning) environment, individual students are guided to learn in a real-world situation with supports or instructions from a computer system or using a mobile device to access the digital content via wireless communications, where the learning system is able to detect and record the learning behaviors of the students in both the real world and the virtual world with the help of the sensor technology (Hwang, Tsai, & Yang, 2008; Ogata & Yano, 2004).

In traditional web-based learning environments, navigation support is an important issue. Researchers have given considerable attentions on flexible curriculum sequencing control to provide adaptable personalized learning programs. Zhao and Wan (2006) described relationships between knowledge units in a graph structure and proposed an algorithm to select the shortest learning path. Chen (2008) proposed a genetic-based personalized learning path generation scheme for individual students to support personalized web-based learning. Researchers found that, an inappropriate navigation support in web-based learning tends to lead disorientation during learning processes, thus reduce learning efficacy. When the paradigm shifts to the context-aware u-learning environments, navigation supports becomes even more important as the student is learning around the real space rather than cyberspace (Chu, Hwang, Huang, & Wu, 2007). In web-based learning environment, all the learning contents in a curriculum are sequenced by hyper links, but there is no concrete sequence in authentic world without navigation support.

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In the u-learning environment, there are many target objects for students to observe and learn about. It is difficult for the students to determine what to visit without any guidance. They might fail to understand the relationships among those target objects. That is, they are likely to be disorientated in the learning process. In conducting learning activities in real-world environments such as museums, ecology gardens or classrooms, researchers have found that the learning quality might be significantly affected if too many people attempt to visit or learn about the same target object simultaneously (Chang, Chang, & Heh, 2007; Din, 2009; Hwang, Kuo, Yin, & Chuang, 2010; Limongelli, Sciarrone, Vaste, & Temperini, 2008). Thus, it is necessary to guide them adequately to visit a target object at the proper time, so that the learning quality for each target object can be better.

There are several concerns while designing an adaptive navigation support system for u-learning activities.

(1) *Capacity limitation*: The learning targets in the learning environment are real-world objects; that is, the number of simultaneous visitors needs to be controlled. The capacity limitation of a learning object will affect the learning quality. For instance, when a crowd of students surround the learning objects in the same time, it is quite possible that most students are not able to clearly observe the learning objects; consequently, the learning quality could be significantly affected.
(2) *Dynamic configuration*: The contexts in a u-learning environment usually change frequently owing to the movements of the students (e.g., number of students in an area and the location of an individual student) and the variant of environment conditions (e.g., temperature, moisture and noise), and hence the learning path need to be scheduled dynamically based on the changes of the personal and environmental contexts (Hwang, Tsai, et al., 2008).
(3) *Immediate response*: As the students are guided to learn in the real world, the learning guidance needs to be provided immediately. When a student finishes his/her learning about one learning objects, he/she should receive further instructions immediately.
(4) *Time constraint*: Most u-learning activities have their time constraints. Students must finish their learning in a pre-given period of time. In most cases, it is difficult to learn all the learning objects exhaustively in time. To obtain a best learning efficacy in a u-learning activity, it is reasonable to learn the most important learning objects first.

It can be said that the adaptive navigation support problem for u-learning is challenging since it is not only an optimization problem, but also a real-time guidance problem. So far, few literatures have discussed the problem. In practical applications, usually a fixed learning path is provided for all of the students without considering personal and environmental situations.

In this paper, we attempt to explore the unique characteristics of navigation support mechanisms for context-aware u-learning and find out the major factors that affect the learning efficacy in such an environment. Moreover, two navigation-supporting algorithms, the Maximized Objective Navigation Support algorithm (MONS) and the GEnetic Navigation Support algorithm (GENS), are proposed to cope with the problem. For fitting the variance of the situations, several experiments were simulated. By comparing the performance of MONS, GENS and Random Assignment with a set of data, it is found that MONS outperforms the others in most of the cases. Moreover, a practical application has shown the benefits of the innovative approach in helping the students to more effectively and efficiently utilize the learning resources and achieve better learning efficacy.

2. Relevant works

Lave and Wenger (1991) indicated that schools are communities of practice with their own formal and informal codes of behaviors, and this traditional learning cannot be regarded as situated since the curricular content is not used by the school community itself. Students find it difficult to apply learned knowledge after schools because learning takes place within the culture of school life instead of the culture where the domain knowledge is used (Brown, Collins, & Duguid, 1989). They preferred the “authentic activities” in which they can work with problems from the real world. Researchers also indicated the importance of enabling students to access educational information flexibly, calmly and seamlessly.

In order to situate students in authentic learning environment, which refers to direct experiences that take place within the context of practice, it is important to place the students in a series of designed lessons that combined both real and virtual learning environments (Hwang, Wu, & Chen, 2007; Minami, Morikawa, & Aoyama, 2004). Context-aware ubiquitous learning is such an innovative approach that enables students to learn anything at anytime in anywhere with personalized support from the digital world (Hwang, Tsai, et al., 2008). In this learning environment, mobile computing, wireless communication and sensor technologies are employed, such that the learning behaviors of students in the real world and environmental contexts can be detected and personalized supports can be provided to assist or guide the students to learning in the authentic environment accordingly.

Several researchers have demonstrated the benefits of context-aware ubiquitous learning in helping students to improve their problem-solving ability in the real world (Chu, Hwang, & Tsai, 2010; Hwang, Tin, Hwang, & Tsai, 2008; Jones & Jo, 2004). For example, Ogata and Yano (2004) presented JAPELAS and TANGO, which have been used to conduct students to learn Japanese under real-world situations. The systems can provide students with appropriate expressions according to different contexts (e.g., occasions or locations) via mobile devices (e.g., PDA – Personal Digital Assistant). Rogers et al. (2005) integrated the learning experiences of indoor and outdoor activities by observation in the working scene. Students not only are capable of getting data, voice and images from the scene by observations, but also of gathering related information from learning activities via wireless networks. Joiner, Nethercott, Hull, and Reid (2006) presented their studies of using context-aware devices applied in education by timely offering vocal statements of activities for students in the real conditions. In the meanwhile, Yang, Huang, Chen, Tseng, and Shen (2006) proposed a learning environment, which stores resources through peer to peer (P2P) model, for encouraging learning resource sharing. Recently, researches also conduct learning activities for training observation and classification abilities of students in content-aware ubiquitous learning environment (Chu et al., 2010).

One of the most challenging issues for providing personalized supports to individual students in a context-aware ubiquitous learning environment is the planning of the learning paths to meet the change of physical learning status of individual students. In the past decade, several personalization mechanisms have been proposed, such as adaptive presentation, adaptive navigation support, curriculum sequencing, and intelligent analysis of student’s solutions (Hwang, 2003; Tang & Mccalla, 2005; Weber & Specht, 1997). Among these personalization mechanisms, adaptive navigation support (ANS) has become especially popular in developing educational hypermedia systems (Brusilovsky, 2003; Chen, 2008; Yudelson, Brusilovsky, & Sosnovsky, 2004).

While the ANS problems have been widely discussed for web-based learning, they are still an important and challenging issue for context-aware ubiquitous learning since the factors needed to be considered in a context-aware ubiquitous learning environment are much more complicated. Hwang et al. (2010) indicated that, capacity limitation and relevance between objects to be visited will significantly affect the quality of learning. However, it is difficult for the visitors who navigate based on their own interest and mental model to take such complex multi-objective optimization into consideration. Therefore, researchers have suggested developing navigation support mechanisms to guide individuals to learn in a more effective and efficient way (Hwang et al., 2010).

In traditional approach, a fixed learning path is usually provided for all of the students without considering personal and environmental situations, implying that all the students will visit the learning objects in the same sequence with the same time constraint. That is, a number of learners will crowd into some learning objects while some objects may not have any visitor. Moreover, the time constraint will prohibit the students from visit all the learning objects or fail to complete the observation of some important learning objects.

Moreover, without proper plan about the learning path, most students might fail to visit some learning targets within the specified period of time. Therefore, it is important and challenging to develop a navigation-support mechanism which guides the students to visit those subject-related learning objects in a given period of time.

Navigation support aims to plan paths for individual students under some criteria and constraints (Fonseca & Fleming, 1995). A learning environment can be formulated to a mathematical model with several factors and constraints, and hence the best solution under the constraints can be determined. Once the problem is formulated to an optimization problem, well-know approaches for optimization, such as *Linear Programming*, *Dynamic Programming*, *Heuristic Algorithm* and *Meta-Heuristic Algorithm* (Cormen, Leiserson, Rivest, & Stein, 2000) can be adopted to find quality solutions. The characteristics of these four algorithms are described briefly as follows:

(1) *Linear Programming*: Linear Programming determines the way to achieve the best outcome of a given objective function, subject to linear equality and linear inequality constraints.
(2) *Dynamic Programming*: Dynamic Programming is a method for solving complex problems by breaking them down into simpler steps. It is applicable to problems that exhibit the properties of overlapping sub-problems and optimal substructure. That is, the solution can be obtained by the combination of optimal solutions to its sub-problems.
(3) *Heuristic Algorithm*: Heuristic Algorithm is an algorithm that is able to produce an acceptable solution to a problem in many practical scenarios. The solution may be correct, but may not be proven to produce an optimal solution, or to use reasonable resources.
(4) *Meta-Heuristic Algorithm*: Meta-Heuristic Algorithm is a heuristic method for solving a very general class of computational problems by combining user-given heuristics.

Based on the major concerns of ANS system for u-learning; that is, *Capacity limitation*, *Dynamic configuration* and *Immediacy of response*, the comparisons on the four types of algorithms are given in Table 1, which shows that the heuristic algorithm seems to be the most promising approach to cope with this problem.

3. Navigation support mechanisms for context-aware u-learning environments

In order to promote the efficacy of context-aware ubiquitous learning, an adaptive navigation support mechanism is needed. In the following subsections, the ANS problem for context-aware ubiquitous learning is formulated, and two navigation algorithms are proposed to find quality solutions of the problem.

3.1. Problem formulation

A context-aware u-learning environment can be perceived as a live scene in which the learning system can detect the status of individual students via sensors (e.g., RFID or GPS) and guide them to visit a set of learning objects via mobile devices. Each learning object has a capacity limitation (i.e., the maximum number of students who are allowed to visit the learning object in the same time) and expected learning time. In addition, it takes time for a student to move from a learning object to another.

Table 1
Evaluation of the four algorithms.

	Resource constrains	Dynamic configuration	Immediacy
Linear programming	○	×	×
Dynamic programming	○	△	△
Heuristic algorithm	○	○	○
Meta-heuristic algorithm	○	○	△

○: Suitable; △: Plain; ×: Unsuitable.

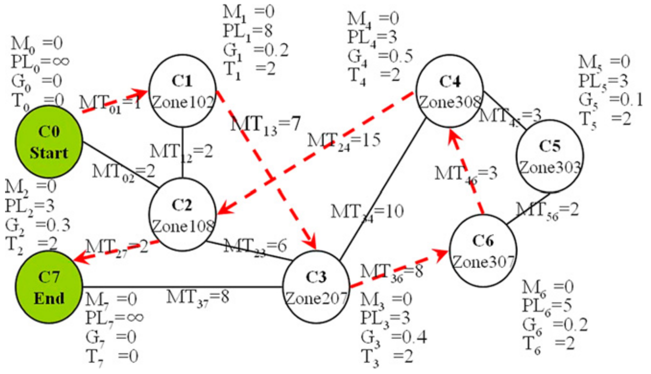


Fig. 1. Graphical representation of a context-aware u-learning environment.

In this study, each learning object is treated as a knowledge asset with an expected learning profit value. The expected learning profit value of each learning object is assigned by the teacher according to the target of the learning activity. The learning system will guide the students to conduct a learning mission (e.g., an observation mission, an operation mission or a Q&A problem) for each learning object. After visiting a leaning object, the students are expected to gain the learning profit. Fig. 1 depicts an illustrative example of the real-time situations for guiding the students to learn various swallowtail butterflies in a butterfly museum. In this example, the specimens of swallowtail butterflies are placed in Zones 102, 108, 207, 303, 307 and 308, and the total time limitation of the learning activity is 60 min, which indicated that the students need to visit all the exhibitions within 60 min. This example will be used for explaining all the algorithms suggested in this paper. The real-time situations of the learning activity can be described by the following parameters:

(1) Environment-related parameters:
- *n:* Number of learning objects.
- C_j: Identification of a learning object, for $j \leqq n$.
- *Eij*: Learning path from C_i to C_j , for $i,j \leqq n$, i ¦ j.
- $MT_{i,j}$: Expected time for moving from C_i to C_j and i ¦ j.
- *LT*: Total time limitation.
- *S*: Acceptable saturation ratio, which is the acceptable percentage of occupied or used capacity for learning objects. This parameter is used to control the number of students who access one learning object in the same time.

(2) Object-related parameters:
- PL_j: Capacity limitation of learning object C_j
- G_j: The expected learning profit of learning object $C_{j.}$ It is a value ranged from 0 to 1. It can be set by teachers based on the relevance of the learning object to the target of the learning activity. If the learning object is nothing to do with the target, the vale will be 0.
- T_j: Expected time for learning C_j.
- M_j: The number of students who are visiting C_j. The value of M_j must be less than or equal to PL_j.
- R_j: Current Saturation ratio of C_j; $R_j = M_j/PL_{j.}$ It represents the ratio of number of students who are visiting C_j to the capacity limitation of C_j.
- F_j: Indicator of fullness of C_j. It is determined by R_j and S. If $R_j < S$ then $F_j = 0$, otherwise $F_j = 1$.

(3) Student-related parameters:

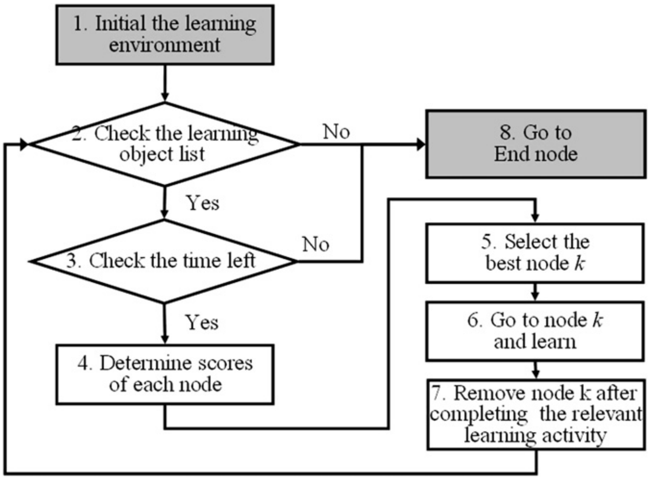

1. Initial the learning environment
2. Check the learning object list
No
8. Go to End node
Yes
No
3. Check the time left
5. Select the best node k
Yes
6. Go to node k and learn
4. Determine scores of each node
7. Remove node k after completing the relevant learning activity

Fig. 2. The flow diagram of MONS.

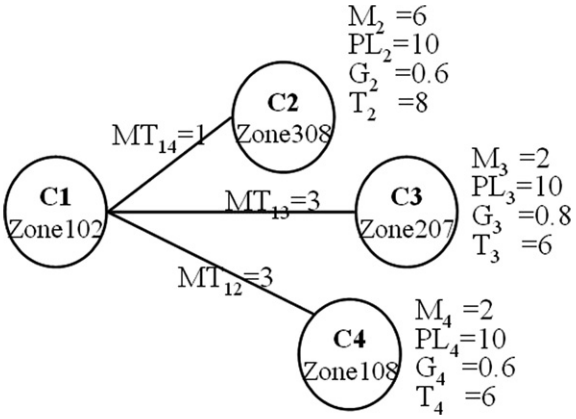


Fig. 3. An illustrative example of MONS algorithm.

- CT_i: Total consumed leaning time of student *i*, which represents the total time already spent by student *i*.
- TP_{ij}: Consumed learning time while student *i* learning object *j*, for $j \in \mathrm{N}, j \leqq n$. This parameter will be used to remind student *i* how long did he/she spend at object *j*.

These parameters will be used to determine the best navigation path. The learning efficacy of a student participated in the learning activity is defined as the total learning profit of the learning objects that the student has visited. A method with higher learning efficacy score means that the method instructs learners to learn more relevance objects than others. In the following section, two navigation algorithms, MONS and GENS, will be introduced.

3.2. The Maximized Objective Navigation Support Algorithm (MONS)

The Maximized Objective Navigation Support algorithm (MONS) is a heuristic-based algorithm where the navigation path can be determined in a short time. The objective of MONS is to immediately provide the learning object for students that costs less time and has large learning efficacy. The flow diagram of MONS is shown as Fig. 2. The process of MONS is given as follow:

Step 1: *Initiate the learning environment*, including parameter configuration and update the learning object list.
Step 2: *Check the learning object list*. If no learning object exists then go to Step 8; otherwise, continue the learning process.
Step 3: *Check the time left*. If there is not enough time to leave after learning then go to Step 8, otherwise continue learning.
Step 4: *Determine scores of each node*. Assume that the current node is C_i, the score for selecting C_j as the next node to visit is determined by the following objective function:

$$Score(i,j) = \frac{G_j \ln[S - R_j] + 1}{MT_{i,j} + T_j} \tag{1}$$

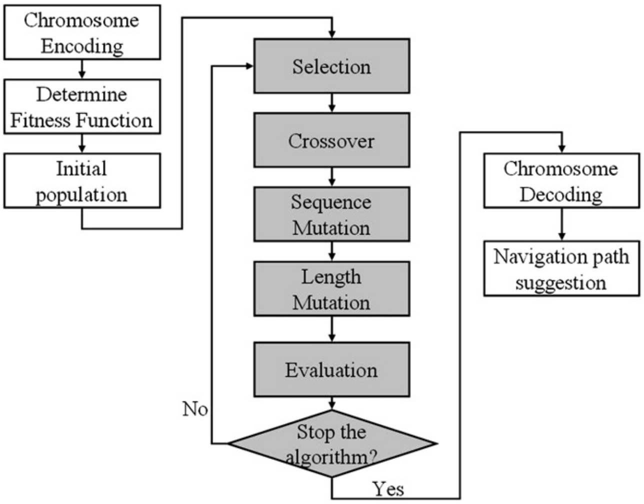


Fig. 4. Flow diagram of GENS.

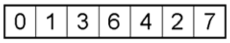


Fig. 5. An example of chromosome encoding.

In this mathematics function, the denominator represents the time spent on moving and learning, and the numerator represents suitability and availability of the target learning object, which is obtained by computing the product of learning profit and the capacity value of the selected object. If the selected object is in a distant location and the time needed to learn the object is long, the denominator value will be large, implying that the final score will be lowered. Moreover, if the selected object is relevant to the learning subject and the capacity is large, the numerator value will be large, implying that the final score will be heightened. To sum up, a higher score implies the learning object is with higher relevance, higher availability and less learning burden.

Step 5: *Select the best node k, which is the node with the highest score.*
Step 6: *Go to node k and learn.*
Step 7: *Remove node k after completing the relevant learning activity, and go back to Step 2.*
Step 8: Go to End node.

An illustrative example based on Fig. 1 is shown in Fig. 3. In this case, the learner has completed the learning mission at C_1 and there is 10 min left for further learning. Assume that C_2, C_3 and C_4 are in the candidate-learning object list and the value of acceptable saturation ratio (S) is 0.8. Based on formula 1, the scores of these candidate-learning objects are obtained as follows:

$$Score(1,2) = \frac{0.6 \times \ln[0.8 - 0.6 + 1]}{1+8} = 0.0122$$

$$Score(1,3) = \frac{0.8 \times \ln[0.8 - 0.2 + 1]}{3+6} = 0.0418$$

$$Score(1,4) = \frac{0.6 \times \ln[0.8 - 0.2 + 1]}{3+6} = 0.0313$$

Consequently, learning object C3 with largest score is selected. In this example, although C2 is the nearest learning object, the learning quality provided at that moment for C2 is low since the number of learners is large and the needed learning time is long. Without the guidance from the learning system, most learners may select C2 as the next learning object and spend the rest time in a low quality learning situation.

3.3. The GEnetic Navigation Support Algorithm (GENS)

The GEnetic Navigation Support algorithm (GENS) is base on the *Genetic Algorithm* (GA) which belongs to meta-heuristic algorithms (Hwang, Tin, et al., 2008; Mitchell, 1996). GA is one of the most intensively-used techniques from evolutionary computation. Based on the Darwinian principle of "survival of the fittest", GA simulates the process that fitter individuals will have a higher probability to survive and pass their genes to the next generation through genetic operations (Holland, 1975). GA has manifested successful applications such as scheduling and time versus cost optimization (Hwang, Yin, Wang, Tseng, & Hwang, 2008).

In this study, each learning object is treated as a gene and the navigation sequence can be formed as a chromosome (Mitsuo & Lin, 2006; Rajeev, Ashwin, Krishna, & Peter, 2008). Note that each chromosome can only have one instance of a gene. The flow diagram of GENS is shown in Fig. 4.

The process of GENS is given as follow:

Step1: *Chromosome encoding*: In this step, a navigation sequence will be encoded as a chromosome. The chromosome is a set of genes which is formed by the serial number of learning objects. For fixing the start and end position, the end-points will be 0 and $n+1$. For example, the navigation path in Fig. 1 is 0→1→3→6→4→2→7 and it will be encoded as shown in Fig. 5.

Step2: *Determine the fitness function*: In order to find out the potential chromosomes (solutions) and preserve them for further generation, a fitness function is needed to evaluate the fitness of a chromosome. The function designed in this study is shown as following:

$$Fitness(X_i) = \sum_{j-1}^{l} [G_x \times (1 - F_x)], where\ x = X_{ij} \qquad (2)$$

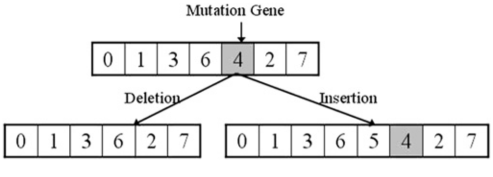


Fig. 6. Illustration of the length mutation operation.

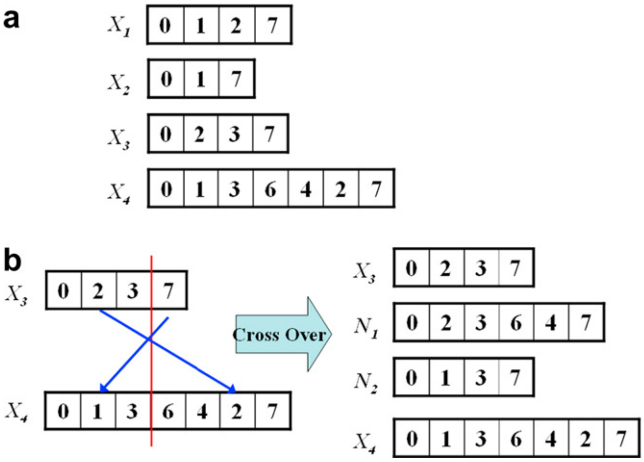

a
X1 | 0 | 1 | 2 | 7
X2 | 0 | 1 | 7
X3 | 0 | 2 | 3 | 7
X4 | 0 | 1 | 3 | 6 | 4 | 2 | 7
b
X3 | 0 | 2 | 3 | 7
X4 | 0 | 1 | 3 | 6 | 4 | 2 | 7
Cross Over
X3 | 0 | 2 | 3 | 7
N1 | 0 | 2 | 3 | 6 | 4 | 7
N2 | 0 | 1 | 3 | 7
X4 | 0 | 1 | 3 | 6 | 4 | 2 | 7

Fig. 7. Initial population and cross over stage in GENS.

In this function, X_i is the *i-th* chromosome in present generation; *l* is the length of the chromosome X_i; $X_{i,j}$, a unique serial number of a learning object, is the *j-th* gene on the *i-th* chromosome; G_x is the learning profit of learning object C_x. and F_x is the indicator of fullness of C_x. Formula (2) is proportional to the learning profit (G_x) and inversely proportional to the indicator of fullness (F_x). That is, the learning path with higher profit and less fullness learning objects is fitter. In addition, some constraints need to be satisfied:

$$2 \le m \le n+2 \tag{c1}$$

$$\sum_{j=1}^{m} T_x + \sum_{j=1}^{m-1} T_{x1,x2} \le LT \text{ where } x = X_{ij}, x_1 = X_{ij}, x_2 = X_{i,j+1} \tag{c2}$$

$$\forall x_i, x_j \in \{x_1 \ldots x_k \ldots, x_m\}, x_i \neq x_j \tag{c3}$$

Constrain (c1) restricts the number of nodes in a navigation path, that is, at least two nodes (Start node and End node) and at most $n+2$ nodes. Constrain (c2) restricts the expected learning time of the generated path being less than or equal to the total time limit. Constrain (c3) is used to prevent duplicate genes in a chromosome. Note that when all the learning objects reach their fullness levels, the value of Fitness (X_i) will be zero. In this case, the leaning nodes which satisfy all the constraints will be considered first.

Step3: *Initial population*: In this step, *P* chromosomes will be generated under constrains (c1)–(c3) and the sequence of genes in these chromosomes will be random. These chromosomes are called initial population.
Step4: *Selection*: In this step, the potential chromosomes will be chosen from a population for next generation. The population will be scored by the fitness function and then the population will be sorted in a decreasing order. In GENS, the former 50% of chromosomes are preserved and the latter 50% of chromosomes are used to generate next generation of chromosomes by *Step5–Step8*.
Step5: *Crossover*: Crossover is used to vary the programming of chromosomes from one generation to the next. One-point crossover is used in this study and the crossover point is randomly selected. If there are duplicated genes in a chromosome, one of them will be replaced by the un-selected gene.

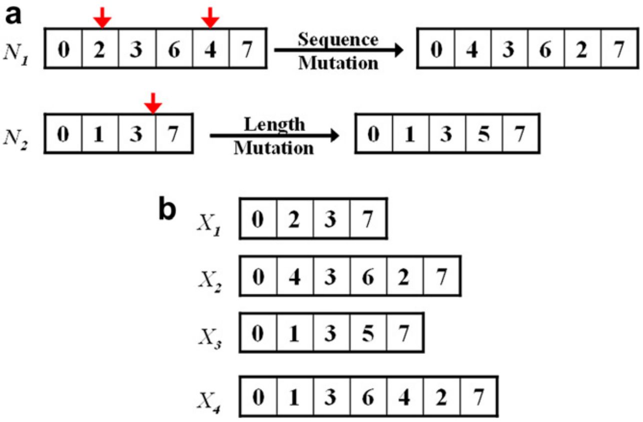


Fig. 8. Mutation and evaluation stage in GENS.

Fig. 9. The butterfly museum.

Step6: *Sequence mutation*: Mutation is used to maintain genetic diversity from one generation of a population. There are two kinds of mutations in GENS and they are sequence mutation and length mutation. When sequence mutation occurred, two selected genes will be exchanged.

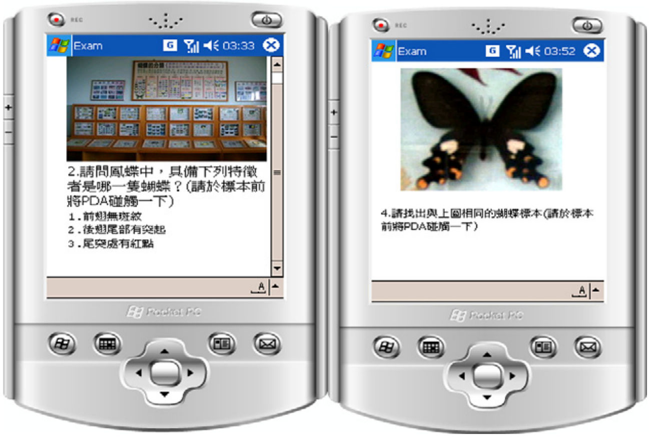
Step7: *Length mutation*: Different from the normal genetic algorithm, the length of a navigation sequence (chromosome) is variable. Therefore, length mutation is used in GENS. Two kinds of length mutation would be occurred in the randomly selected gene position. They are deletion and insertion, and the occurrence probabilities of them all equal to 50 percent. The illustration is shown as Fig. 6.

Step8: *Evaluation*: The results from previous processes will be examined by the fitness function. Potential chromosomes will be preserved for the next generation.

Step4–Step8 is the process of one generation. If the termination criterion of GENS has been satisfied, the most potential chromosome will be output as the result, otherwise go back to Step 4 and run the evolution process again. In this study, the termination criterion is that the number of generations is reached the given value.

Step9: *Chromosome decoding*: Decoding the chromosome into a navigation path, and then suggest it to the learner.

Consider the illustration example given in Fig. 1. There are six learning objects to be observed and the time limitation is 40 min; moreover, C1 and C7 are the first and the last learning objects to be visited, respectively. For simplifying, we set the initial population to 2 and terminate the algorithm after one generation. Without loss of generality, four chromosomes are generated in each generation of the GA program. Initially, four parent chromosomes are generated randomly, as shown in Fig. 7(a). The fitness degree of each chromosome is then determined as follows:



2.請問鳳蝶中，具備下列特徵者是哪一隻蝴蝶？(請於標本前將PDA碰觸一下)
1.前翅無斑紋
2.後翅尾部有突起
3.尾突處有紅點

4.請找出與上圖相同的蝴蝶標本(請於標本前將PDA碰觸一下)

Fig. 10. Proposed interface of the adaptive navigation system.

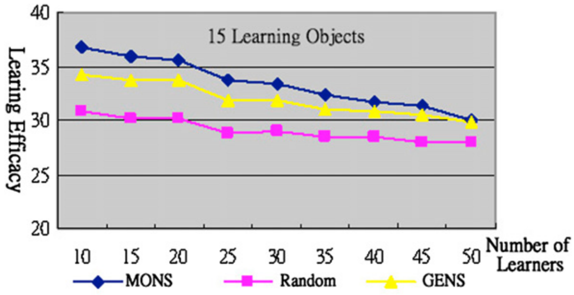


Fig. 11. Learning efficacies with 15 learning objects.

$$Fitness(X_1) = 0.2 + 0.3 = 0.5$$

$$Fitness(X_2) = 0.2$$

$$Fitness(X_3) = 0.3 + 0.4 = 0.7$$

$$Fitness(X_4) = 0.2 + 0.4 + 0.2 + 0.5 + 0.3 = 1.6$$

The chromosomes with high fitness degrees (i.e., X_3 and X_4) will be selected in the "cross over" stage, in which the new chromosomes (N_1 and N_2) will be generated by randomly selecting a cutting position for exchanging the genes of the selected chromosomes. The new chromosomes after "cross over" operation are shown in Fig. 7(b).

Fig. 8(a) shows an illustrative example of the Mutation stage, in which Sequence Mutation and Length Mutation are occurred randomly. In this example, N_1 mutates by exchanging two randomly selected values (i.e., "2" and "4") and N_2 mutates by extending its length. The new chromosomes as shown in Fig. 8(b) are then evaluated by the fitness function to determine if they are better than the original ones. The fitness degree of each chromosome is determined as follows:

$$Fitness(X_1) = 0.3 + 0.4 = 0.7$$

$$Fitness(X_2) = 0.2 + 0.4 + 0.2 + 0.3 = 1.1$$

$$Fitness(X_3) = 0.2 + 0.4 + 0.1 = 0.7$$

$$Fitness(X_4) = 0.2 + 0.4 + 0.2 + 0.5 + 0.3 = 1.6$$

In this example, the fitness navigation sequence (X_4) 0→1→3→6→4→2→7 will be suggested.

4. Experiments and evaluations

An adaptive navigation support system is developed based on the innovative approach. Moreover, the "Butterfly Classification" unit of a Natural Science course is used to demonstrate the learning scenario for applying the proposed algorithms. In this course, the students learn the features of butterflies, and identify them accordingly. Fig. 9 shows the butterfly museum, in which hundreds of butterfly samples (learning objects) are exhibited. Each time the students are asked to observe a part (5, 10, 15 or 30) of the butterfly samples according to the subject plan.

To evaluate the performance of the optimization algorithms, a set of test data is executed in a simulation environment to evaluate the efficacy and immediacy of our algorithms. Such an evaluation procedure has been widely used by many researches that are relevant to optimization problems for practical applications, and as been recognized to be effective and efficient (Ho, Yin, Hwang, Shyu & Yean, 2009; Hwang, Lin, & Lin, 2006; Hwang, Yin, et al., 2008; Yin, Yu, Wang, & Wang, 2007). Only when the simulation results show the effectiveness of

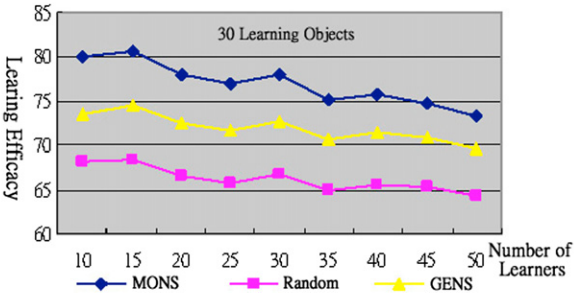


Fig. 12. Learning efficacies with 30 learning objects.

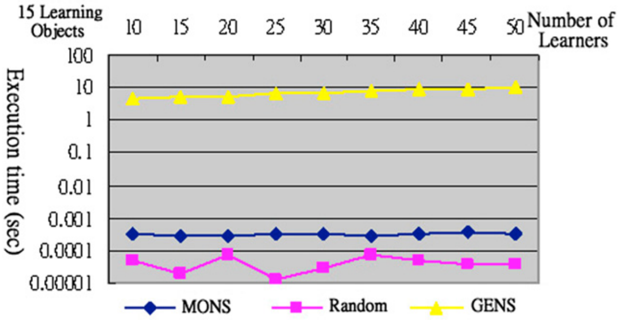


Fig. 13. Execution time for 15 learning objects.

the proposed algorithm is available, further experiments on practical applications needed to be performed. Fig. 10 shows the proposed interface that can be implemented once the best navigation algorithm is identified through simulated data.

Three algorithms are used to compare the average learning efficacy and execution time; that is, Random Selection (abbreviated as Random), MONS and GENS. The experiments were conducted on a computer with Intel Pentium4 3.0 GHz and 1 GB RAM.

To reflect the practical applications of the navigation system, the number of learning objects in the experiment is ranged from 5 to 30 and the number of students ranged from ten to thirty. One hundred cases are used to test each situation. Moreover, the time for a student to observe a learning object is ranged from 5 to 20 time unit, and the maximum capacity of each learning objects (the number of students allowed to observe the same object) is ranged from 1 to 10. The expected learning profit value of a learning object is ranged from 1 to 5, and the time needed for the students to walk to the next learning objects is ranged from 1 to 20 time unit.

In order to approach the realistic applications, the students are allowed to leave the node earlier or later than the setting and walk faster or slower than the setting. Moreover, the configurations of algorithms are given as follows:

- *Random*: The learning objects along the navigation path will be selected randomly. Each selection will select the learning object with the highest expected learning profit among 10 randomly selected candidates.
- *MONS*: The Saturation Ratio is set to 80. It means that a learning object is considered to be full when 80% of its capacity is occupied. The setting allows some visitors who are not guided by the navigation support system to visit the learning object.
- *GENS*: Population of each generation is 100. Initial length of each chromosome is adjusted by time left. The probabilities of one-point crossover, one-point mutation and length mutation are 1.0, 0.5 and 0.1 individually. The termination criterion is set to 50 generations.

Results of average learning efficacy of the three algorithms are shown in Fig. 11 and Fig. 12. From the figures, MONS outperforms GENS, and GENS outperforms Random. It is interesting to find that GENS, a GA-based meta-heuristic algorithm, does not outperform MONS, a heuristic algorithm. In previous study of optimization algorithms, meta-heuristic algorithms usually outperform heuristic algorithms. These contradictions might due to the dynamic nature of the underlying problem. Since the behaviors of students in a u-learning environment are unpredictable (for example, it is quite possible that the time for a student to visit a learning object is longer or less than being expected), the real configurations might be quite different from the settings in GENS while it was used to determine the best learning path. Therefore, the best learning path found in GENS is no more the best when a student needs the navigation support.

Figs. 13 and 14 show the execution efficiencies of the three algorithms. It can be seen that Random outperforms MONS, and MONS outperforms GENS. The results are straight forward since Random conducts the least operation while the computation process of GENS is the most complicated.

Note that the execution time of MONS is almost as efficient as Random while its average learning efficacy is much higher than Random. In addition, it is obvious that GENS is not efficient and is not suitable for supporting real-time applications. Therefore, we conclude that MONS is a better navigation support algorithm for context-aware ubiquitous learning. The comparison results of the three algorithms are given in Table 2.

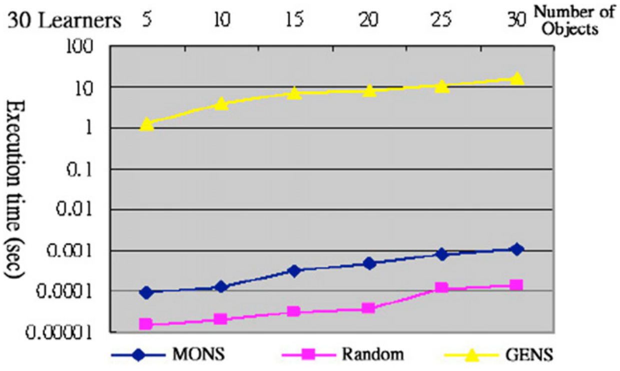


Fig. 14. Execution time for 30 learners.

Table 2
Comparison of learning efficacy in different algorithms.

Condition	Algorithm		
	Random	MONS	GENS
Less object/less student	Low	High	Medium
More object/less student	Low	High	Medium
Less object/more student	High	Low	Medium
More object/more student	Low	High	Medium

5. Conclusions and future works

In order to situate students in real-world learning environment, which refers to direct experiences that take place within the context of practice, it is important to place the students in a series of learning activities that combine both real and virtual learning environments Context-aware ubiquitous learning aims to develop such a learning environment to provide students with real-world experiences and knowledge. Few literatures have discussed the navigation problem in context-aware ubiquitous learning environment.

In this paper, learner and environmental related parameters for ubiquitous learning are analyzed and two heuristic-based navigation algorithms GENS and MONS are proposed for guiding the students to learn in the real world. From the experimental results with a set of simulation data, it is found that MONS outperforms than other algorithms. MONS not only maintains the learning quality by controlling the number of students in each learning area and guiding them to learn in the most logical way, but also has the benefits of being efficient and easy to implement.

It should be noted that the navigation problem defined in this paper could be used to guide students to learn in a very large learning area, such as the national park and the palace museum. The algorithms can also be employed in advance applications such as subject-oriented learning, adaptive learning, trip planning, and etc. Moreover, as several environmental parameters, such as the distance between each pair of learning objects and the expected time needed to complete the mission item associated with each learning object, the benefits of the innovative approach could be more significant for larger learning area with more target objects.

Currently, we are planning to conduct several large-scale experiments in National Museum of Nature Science in middle Taiwan. Nearly one-hundred of elementary school students will be invited to participate in the learning activities concerning nature science exploration. The results of the experiments will be used to further evaluate the effectiveness of the innovative approach.

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