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An Adaptive Sequencing Method of the Learning Objects for the e-Learning Environment

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SUMMARY

In this study, an e-learning system is developed to handle the e-learning environment based on the learning ecological model. In the learning ecological model, which represents the comprehensive e-learning environment, not only the contents of learning, but also the learning environment are managed and provided, based on the content, the goal, and the configuration of the learning. The major purpose of this study is to realize the function that can manage the diversified learning objects with various information granularities and representation formats, using the learning object metadata, so that each learner can utilize the learning object based on the learning scenario, which is matched to the individual learner. The learning scenario is constructed by sequencing the learning objects based on the learning necessity, the learning history information, and the curriculum information of the object of learning, according to the characteristics of the learning object. As the sequencing procedure, the sequencing of the learning objects is considered, by applying the optimization technique of the multi-objective optimization problem, so that multiple evaluation viewpoints are simultaneously satisfied. The genetic algorithm is used as the optimization procedure. The learning object metadata and the sequencing of the learning objects are discussed in detail in this paper. The evaluation of the developed e-learning system is also described. © 2004 Wiley Periodicals, Inc. Electron Comm Jpn Pt 3, 88(3): 54–71, 2005; Published online in Wiley InterScience (www.interscience.wiley.com). DOI 10.1002/ecjc.20163

Key words: remote learning; sequencing of learning objects; LOM; multi-objective optimization problem; genetic algorithm.

1. Introduction

With the recent widespread use of the Internet, the learning (education) environment called e-learning is considered as necessary and important, both in and out of this country. e-learning includes the individual asynchronous learning configuration, such as WBT/L (web-based training/learning), as well as simultaneous synchronous learning using the network conference system. There is also the cooperative learning configuration combining the synchronous and asynchronous configurations. The e-learning environment is based on the distributed cooperative learning environment.

In such a learning environment, it is important that the positive learning activity of the learner be included. The following conditions must be satisfied for this purpose.

① There should be a framework by which anybody can learn at any time and anywhere.

② Guidance information/diagnostic information should be provided based on the learning history information (achievement record information).

③ There should be an educational evaluation function (portfolio assessment) that diagnoses the performance of the learner.

Based on such a recognition, we have been developing RAPSODY (Remote and AdaPtive educational System Offering DYnamic communicative environment), which is a comprehensive learning-assist system in e-learning environment [1]. In RAPSODY, the learning unit, which is composed of the learning content to achieve the learning goal and the learning configuration suited to the achievement (learning procedure, method, and tool), is considered as the learning object. The learning objects are managed as the learning object metadata, called "CELL."

This study focuses on the retrieval of the learning object. The adaptive sequencing of the learning objects is intended, considering the learning object metadata, the learning necessity information, the learning history information, and the curriculum information of the object of learning. The sequencing is not based on the content of the learning object, but is based on the metadata managing the learning objects, which is developed in various representation formats.

In this study, the learning object is composed of learning material units with a relatively coarse granularity, as in WBT/L learning material. There are studies of sequencing the learning materials, on the other hand, where the learning objects of small granularity, such as the learning (teaching) items, are handled [3, 8]. In those studies, a single evaluation parameter is usually considered for sequencing.

In contrast, in this study, the multidimensional information contained in the learning object is utilized, and we attempt to generate adaptively the learning object sequence matched to the learner by applying multiple evaluation parameters (evaluation viewpoints). More precisely, a sequencing procedure is proposed, by formulating the evaluation viewpoint for sequencing as a multi-objective optimization problem. The genetic algorithm (GA) is applied to sequencing. The multipoint search by GA is an effective optimization technique for realizing efficient search of the solution. In addition, by using the distributed GA, an interactive sequencing is realized, by which the learner can intervene in the solution search process.

2. Purpose of This Study

In this study, the e-learning system is developed, which is based on the learning ecological model [15] representing the e-learning environment. The learning environment model (LEM) is a model which represents the comprehensive e-learning environment. It manages and provides not only the learning content, but also the learning environment, based on the learning content, the learning goal, and the learning configuration. Figure 1 shows the concept of LEM. The sequencing of the learning objects,

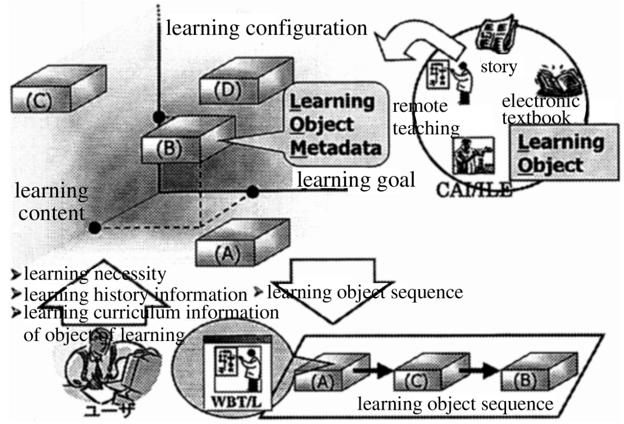


Fig. 1. Learning ecological model.

which is the main topic of this paper, is characterized as the important function in LEM.

RAPSODY includes the implemented procedure, which determines the learning object to be provided to the learner, based on the learning scenario described beforehand by the learning material composer. This study is based on the result of RAPSODY, and develops the e-learning system, which has the function to generate dynamically the learning scenario.

The following functions are implemented in this study:

(1) The function to generate the learning object sequence

(2) The function to correct the learning object sequence

(3) The function to guide the learning

In (1), the sequencing of the learning objects matched to each learner is executed, based on the learning object metadata information, the learning necessity of the learner, the learning history information, and the curriculum information of the object of learning. In (2), it is intended to reflect positively the intention of the learner, and the function is provided for the stepwise interaction between the system and the learner, so that the learning object sequence can be corrected. (3) guides the adequate learning activity, using the learning scenario represented by the learning object sequence.

This paper is structured as follows. Section 3 describes the learning object metadata considered in this study. Section 4 presents the configuration of the e-learning system developed in this study. Section 5 discusses the sequencing of the learning objects. Section 6 gives the evaluation of the system and a discussion.

3. Management of Learning Objects Based on Learning Object Metadata

In this study, the features of the learning object are described as the learning object metadata, and the diversified learning objects in the e-learning environment are managed. This section describes the learning object metadata considered in this study.

The tremendous amount of resources on the WWW (World-Wide Web) includes a large number of contents with useful information, such as the learning material, the electronic text composed for the learning activity, and CAI (computer-assisted instruction)/simple simulation material. By the reuse of those resources as the learning objects, the cost of developing the learning material is reduced. As another advantage, a learning environment is realized in which the learner can learn the same learning content using multiple learning objects, in order to promote the understanding of the learner from multiple viewpoints.

When the existing learning objects are used, however, the crucial points are the management of the diversified learning objects, and the composition of the learning material, in which the learning objects with various information

Table 1. Attributes of learning object metadata

Attribute item			Description format	Value space	Example
discriminating information			auto	natural number	104
recorded information			auto	attribute item in author table (discriminating information)	****
taxon			multiple choice	unit items (11 items) specified in teaching guide for information B in ordinary subject “information”	“structure of fact and simulation”
keyword			free description	—	problem solving, modeling, and simulation
explanation			free description	—	(omitted)
level			multiple choice	“beginner,” “middle,” “expert”	“beginner”
learning time			free description	—	2.5 (2 1/2 hours)
learning action	classification		multiple choice	unit items (11 items) specified in teaching guide for information B in ordinary subject “information”	acquisition of knowledge and skill for information collection and organization
	action		multiple choice	experiencing activity (85 items) needed for achieving learning goal	“observation of fact”
learning configuration			multiple choice	“class learning,” “individual learning,” “search learning,” and “group learning”	“search learning”
execution condition for learning object	kind		multiple choice	“hardware,” “software,” and “others”	“software”
	product		free description	—	“WWW browser”
	Version		free description	—	5.50
position information of learning object			free description	—	******
evaluation	summary		free description	—	(omitted)
	verification problem	problem type	multiple choice	“description” and “multi-choice”	“description”
		problem/correct answer	free description	—	Using table calculation software, collected information is organized and summarized as a report

(content) granularities and expressions are combined. There are studies in which the features of the learning object with various information granularities and representation formats are represented as the learning object metadata, and are managed in a systematic way [5, 9]. There is also a study to reduce the load in describing the learning object metadata [4]; and a study trying to remedy the differences among the learning objects, using a method that conceals the information inherent to the learning object and adds complementary information to the content [13].

The standardization of the e-learning system, on the other hand, is making progress [2, 12]. In that project, the specification is considered for sharing and reuse of the learning object among different kinds of e-learning systems, as well as for exchanging of the learner information (including the learning history information). In order to realize the sharing and reuse of the learning object, learning object metadata (LOM) is proposed.

In LOM specification, 60 attribute information items are defined, by which the learning objects are classified according to educational/technical aspects. In this study, the attribute items, which should be applied in realizing the e-learning system proposed in the next section, are selected from LOM specifications. Other necessary attribute items are newly added, and the concept schema for the learning object metadata is constructed. Table 1 shows the attribute information items used for the learning object metadata in this study.

The action and evaluation in the learning action shown in Table 1 are the attribute items inherent to this study (the classification has the same meaning as the "learning goal" in LOM specification). The action is the information that indicates the actual learning activity (action), which the learner can execute utilizing the considered learning object. It is considered that a learning goal is achieved when the learner executes multiple actions. LOM specifications, however, do not include the attribute item describing the precise action of the learner toward the learning goal.

In this study, in order to present the relation between the learning goal and the learner's action, the above attribute item is prepared. The evaluation is the information which is used to verify the extent of understanding for the learning object tried by the learner. In the reuse of the existing learning object, the referral history, such as the referral time for the learning object (entity of URL information), can easily be acquired. It is difficult, however, to evaluate the extent of understanding for the content of the learning object. For this point, in this study, a series of questions for the feature and verification of the learning object is registered as the learning object metadata, so that the understanding of the learner can be verified.

In this study, the sequencing of the learning objects is executed, considering the logical flow and context of the learning. The logical flow and context of the learning are provided based on the parameter information representing the curriculum information of the object of learning. The details are given in Section 5.3.

4. System Configuration

The e-learning system developed in this study is composed of the learning object sequencing module and the interaction module. Figure 2 outlines the procedure in the considered system.

The learning object sequencing module executes sequencing of the learning objects, using the learning information metadata described in Section 3, as well as the following information.

- The curriculum information of the object of learning:
  The curriculum information consists of "relations among unit items," "presupposition for unit item," "difficulty of unit item," and "adequateness of unit item."
- The learning necessity information:
  The learning necessity information is represented as in Table 2.
- Learning history information:
  The learning history information is represented as in Table 3.

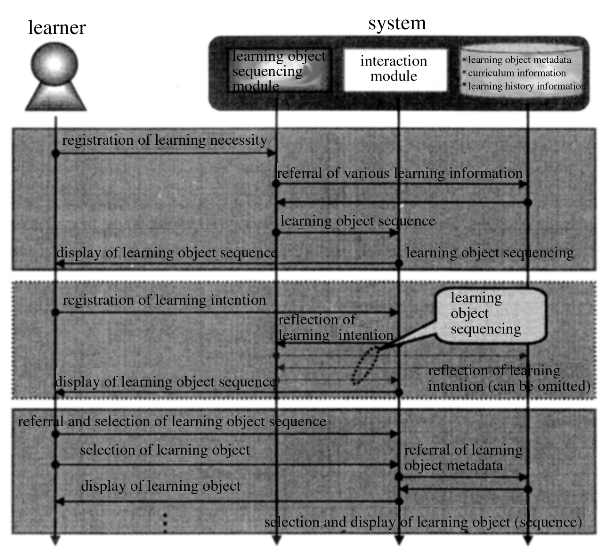


Fig. 2. System procedure.

Table 2. Attributes of learner's needs

Attribute item	Description format	Value space	Example
learning content	multiple choice	unit items (11 items) specified in teaching guide for information B in ordinary subject	"structure of fact and simulation"
learning goal	multiple choice	unit items (11 items) required in information B in ordinary subject "information"	"acquisition of knowledge and skill for information collection and organization"
learning configuration	multiple choice	"simultaneous learning," "individual learning," "search learning," and "group learning"	"individual learning"
level	multiple choice	"beginner," "middle," and "expert"	"beginner"
keyword	free description	—	"information exchange" and "analysis of data"
learning time	free description	—	1.5 (h)

Table 3. Attributes of learner's information

Attribute item		Value space	Example
basic information	user ID	—	"demo"
	name	—	"demo"
	E-mail	—	"demo@p-ai.is.uec.ac.jp"
equipment information	hardware	(omitted)	"DOS/V machine," "PC camera" "microphone"achievement
	software	(omitted)	"Microsoft Office 2000," "Internet Explorer5.5"
achievement of each unit time	taxon	unit items (11 items) specified in teaching guide for information B in ordinary subject	"structure of fact and simulation"
	achievement	[,01]	"0.6"
learning history information	discriminating information for learning object metadata in DB	learning object metadata in DB	"104"
	date	—	"2002-02-22"
	learning time	—	"1.5" (1 hour and a half)
	understanding of verification problem	integer in [1, 5]	"4"
product information	discriminating information for learning object metadata in DB	learning object metadata in DB	"68"
	URL of product	—	"http://192.168.209.62/portfolio/demo/68/rep.doc"

The processing in the learning object sequencing module is as follows. The details of the sequencing are given in the next section.

[step 1] Acquisition of learning necessity information (Table 2).

[step 2] Retrieval of learning object metadata in the database, based on the learning necessity information.

[step 3] Sequencing of learning objects based on the information in step 2 (multiple learning object sequences are generated).

[step 4] The learning object sequence is sent to the interactive module.

The interactive module displays the multiple learning object sequences generated by the learning object sequencing module to the learner. Based on the learning object sequence selected by the learner, the module presents the learning object to the learner. The above is the basic procedure in the interaction module.

The proposed system implements the additional function that positively reflects the learning necessity of the learner. This function is executed between the "sequencing of the learning objects" and the "selection/display of the learning object" processes in Fig. 2. This processing to reflect the intention information (Fig. 2) may or may not be executed.

The learning object sequencing module generates the learning object sequences from four kinds of evaluation viewpoints. The four evaluation viewpoints are weighted equally in this process, but the weight of the evaluation viewpoint can be modified in the interaction module. By this process, the learner can positively reflect his learning necessity on sequencing. For example, a learner who likes learning emphasizing the integration of unit items, can define a weight emphasizing the "relations among unit items."

In this paper, the four parameters to be manipulated by the learner are called "intention information" of the learner. The intention information is sent to the learning object sequencing module through the interaction module. The learning object sequencing module modifies the priorities of the evaluation functions, based on the intention information, and reconsiders the learning object sequence. The intention information and the sequencing procedure to reflect intention information are described in detail in Section 5.6.

5. Sequencing of Learning Objects

This section characterizes the sequencing procedure in this study, through comparison to the preceding studies. In this study, the learning object sequence is generated that satisfies simultaneously the multiple evaluation viewpoints, by applying the genetic algorithm, which is one of the multi-objective optimization techniques.

5.1. Characterization of sequencing procedure

This study assumes the learning environment, in which the learning object to compose the learning object sequence can be registered at any time. In such a case, rather than preparing all learning object sequences using all registered learning objects, it will be more effective to generate dynamically the learning object sequence based on the registration situation of the learning objects at the time.

When a teacher (or expert), on the other hand, composes the learning object sequence, he will compose the sequence through simultaneous evaluation from multiple viewpoints. Thus, the sequencing problem in this study can be handled, being formulated as a multi-objective optimization problem. In this approach, evaluations are attempted from multiple viewpoints, based on the sequencing process. In other words, the necessity and importance of formulation as the multi-objective problem are discussed.

In the preceding studies, the sequencing procedure based on the relative position relations among the learning contents, as well as the sequencing procedure based on the relations among learning contents, are proposed [3, 8]. In the former approach, however, it is difficult to generate the sequence maintaining the logical flow and the context of the learning. In the latter, it is difficult to generate the sequence in which an arbitrary learning content is placed with priority.

It is considered in this study that the sequencing maintaining the learning flow and context is important, even in the case where the easy learning content is to be included with priority. It is also considered that the learning flow and context is the important information for the systematic learning of the learning contents of the object of learning, and has a large effect on the easiness of learning for the learner. In order to realize such sequencing, both the evaluation viewpoint based on the position relation, and the evaluation viewpoint based on the relation among the learning contents must be satisfied.

In the sequencing in this study, the presupposition of the unit item is evaluated, as the evaluation viewpoint for the learning flow and context for the unit item, and the adequateness of the learning action is considered, as the evaluation viewpoint for the matching to the learner's action. As the evaluation viewpoint for the relative position relations among the unit items, the relations among the unit items and the difficulty of the unit item are considered.

A framework is implemented for generating dynamically the learning object sequence based on those evaluation viewpoints. A framework is also proposed where multiple learning object sequences are determined and the learner selects the learning object sequence, not the framework, in which the unique learning object sequence is determined and is presented to the learner.

5.2. Computation model

There are recent studies of the multi-objective GA, which applies GA as the optimization technique in the multi-objective optimization problem [7, 11]. In the multi-objective GA, the solution search progresses, preserving the individuals in parallel, which are considered to have the good quality for respective evaluation functions. It is pointed out, however, in the multi-objective GA that the individuals emphasizing a particular objective function occupy the majority, and the diversity of the individuals is lost.

For this problem, the distributed GA is used, being combined with the multi-objective GA, as a means to maintain the diversity. In the distributed GA, the original set is divided into multiple subsets, and GA operator is applied independently to each subset. In each subset, the operations of {selection, crossover, mutation} are iterated, to grow the individuals. In addition, "migration" is used as an operation inherent to the distributed GA.

The migration is the following process. The individual meeting a certain criterion (called migrating individual) is selected from each subset, and the selected individuals are exchanged between subsets. This is the operation to derive the individual satisfying comprehensively the multiple objective functions, through the process in which the individual grown in a subset is reevaluated in another subset, and the individuals grown in different subsets experience the crossover. It is known that the diversity of the original set is maintained in this process [10, 14].

Based on the above considerations, the computation model, which is a hybrid model of the multi-objective GA and the distributed GA, is implemented in this study (Fig. 3). $f_1(Cs), f_2(Cs), \ldots, f_n(Cs)$ in Fig. 3 are the adaptability functions, which are used in the evaluation of individuals in GA. Four kinds of evaluation viewpoints are used in this study; consequently, $n = 4$.

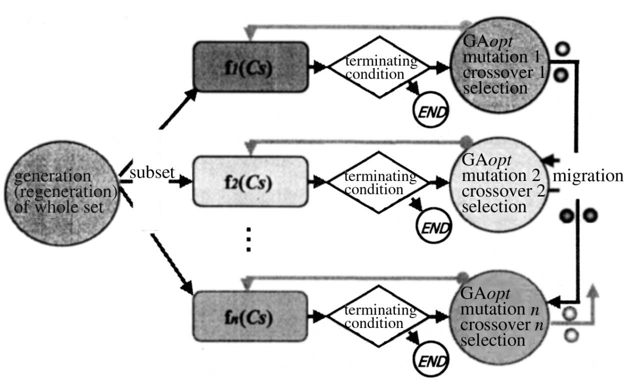


Fig. 3. Computing model of GA.

5.3. Adaptability function

5.3.1. Coding of problem and generation of initial set

By coding of the problem is meant the correspondence between the set of solution candidates and the set of individuals. In this study, the solution candidate, that is, the individual to be evaluated in the GA computation model in Fig. 3, is defined as follows.

The individual (Cs) is represented as a sequence of attribute values (real number) of the "discriminating information" of the learning object metadata. The order of the discriminating information is the order by which the learning object metadata is developed (presentation of the learning object) in the learning.

The adaptability function is calculated as follows. Using the discriminating information, the learning object metadata to be calculated is retrieved from the database. Then, the adaptability function is calculated referring to the attribute values.

The initial set is generated as follows.

[step 1] Based on the learning necessity information, the learning object metadata are retrieved from the database.

[step 2] From the retrieved results in step 1, L learning object metadata are selected at random and arranged.

[step 3] The set obtained in step 2 is divided equally to the number of adaptability functions, and the subsets are constructed (L corresponds to the individual length).

In the above, step 2 is executed up to the size of the set.

In the following, the learning object metadata as the component of the individual (Cs) (Table 1) is written as LOM.

5.3.2. Evaluation function

Evaluation function for relations among unit items

The relation among the unit items is the evaluation viewpoint of "sequencing related unit items with priority." More precisely, the relation between unit items is represented using the binomial relation. The relation between unit item X and unit item Y is given as follows:

$$R(X,Y) = \begin{cases} [0,1] & (X \neq Y) \\ 1 & (X = Y) \end{cases}$$

where $R(X, Y) = R(Y, X)$.

The evaluation function *Relation* (*Cs*) is formulated as follows, using $R(X, Y)$:

$$Relation(Cs) = \frac{\sum_{i=1}^{L-1} R(LOM_i{\rightarrow}Taxon, LOM_{i+1}{\rightarrow}Taxon)}{L-1}$$

where

L: length of individual

i: position on Cs

$LOM_i \rightarrow Taxon$: attribute value of i-th LOM "unit item and subject (taxon)" (name of unit item)

Evaluation function for presupposition of unit item

The presupposition of the unit item is the evaluation viewpoint that "an arbitrary unit item is defined as the reference, and the unit items to be learned before that item are sequenced before it." More precisely, the presupposition of the unit item is represented using the binomial relation. The presupposition of unit item Y in regard to unit item X is given as

$$P(X,Y) = \begin{cases} [0,1] & (X \neq Y) \\ 0 & (X = Y) \end{cases}$$

where $P(X, Y) \neq P(Y, X)$.

The evaluation function *Presupposition* (*Cs*) is formulated as follows, using $P(X, Y)$:

$$Presupposition(Cs) = 2 \times \frac{\sum_{i=2}^{L} \sum_{j=1}^{i-1} P(LOM_i{\rightarrow}Taxon, LOM_j{\rightarrow}Taxon)}{L(L-1)}$$

where i and j are positions on Cs.

Evaluation function for difficulty of unit item

The difficulty of the unit item is the evaluation viewpoint that "the sequencing should be from the easier unit items gradually to the more difficult items." More precisely, the difficulty of unit item X is given as

$$D(X) = [0,1]$$

The evaluation function *Difficulty* (*Cs*) is formulated as follows, using $D(X)$:

$$Difficulty(Cs) = 2 \times \frac{\sum_{i=1}^{L} i \times D(LOM_i{\rightarrow}Taxon)}{L(L-1)}$$

By multiplying the position (i) of LOM with the difficulty, the evaluation value becomes higher, as the unit item with a higher difficulty is placed in the later part of the individual.

Evaluation function for adequateness of learning action

The adequateness of the learning action is the evaluation viewpoint that "the learning of an arbitrary unit item is sequenced based on the competence model." The competence model is described in this study based on the relation between the action processes in the learning. The action process is the learning action which is executed by the learner in order to understand the unit item. The relation between action processes is the flow of actions (transition relation). Figure 4 is an example of the competence model concerning "information acquisition and organization."

The relational structure of the competence model is formulated as follows:

$$A(Act_X, Act_Y) = \begin{cases} 1 & (Act_X{\rightarrow}Act_Y \in Competency) \\ 0 & (Act_X{\rightarrow}Act_Y \notin Competency) \end{cases}$$

where

$Act_X \rightarrow Act_Y$: transition relation from action process Act_X to Act_Y

Competency: all transition relations in competence model

The evaluation function *Activity* (*Cs*) is formulated as follows, using $A(Act_X, Act_Y)$:

$$Activity(Cs) = \frac{\sum_{i=1}^{L-1} A(LOM_i{\rightarrow}Activity, LOM_{i+1}{\rightarrow}Activity)}{L-1}$$

where $LOM_i \rightarrow Activity$ is the attribute value of "action" in the i-th LOM (action label).

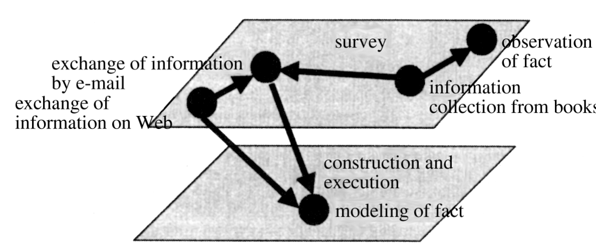


Fig. 4. Example of competency model.

It is assumed that the above condition expressions $\{R(X, Y),\ P(X, Y),\ D(X),\ A(Act_X,\ Act_Y)\}$ are described beforehand by the teacher (or expert).

5.4. Reflection of learning history

Table 3 shows the attribute information of the learner information used by the system in the management of the learner. The learning history is reflected based on the learning history information of the attribute information. The learning history information consists of the following information: the information "discriminating information" to record the utilized learning object metadata, the information "date" to record the date of use, the information "time" to record the time of using the learning object as the learning material, and the information "understanding of verification problem" to record the extent of understanding of the learning object.

When the learner learns a learning object, the information containing the attribute is recorded. Then, the learning history is reflected, by reflecting the learning history information on the evaluation function described in Section 5.3.2. More precisely, the overlap is examined between the learning object metadata recorded in the "discriminating information" of the learning history information and the learning object metadata assigned to the individual (Cs). The overlap is determined based not only on the match of the "discriminating information," but also on the similarity between the learning object metadata.

The similarity is calculated, using "subject/unit item," "learning action," and "level" of the learning object metadata. $C(X, Y)$ below is the expression to represent the match of the attributes. The calculated similarity is multiplied with the inverse of the value recoded in the attribute "understanding of verification problem." The overlap calculated in this way is multiplied with the adaptability function as the weight. This weighting avoids the situation in which a learning object with learning similar to the already understood unit item or learning action is assigned to the individual (Cs).

The function $W_{LH}(Cs)$ to calculate the weight is formulated as

$$\begin{aligned} & W_{LH}(Cs) \\ & = 1 - \frac{1}{3 \times H \times L} \sum_{i=1}^{L} \sum_{j=1}^{H} \frac{1}{data[j].Achieve} \times \{ \\ & \qquad C(LOM_i \rightarrow Taxon,\ data[i].LOM \rightarrow Taxon) \\ & \quad + C(LOM_i \rightarrow Activity,\ data[i].LOM \rightarrow Activity) \\ & \quad + C(LOM_i \rightarrow Level,\ data[i].LOM \rightarrow Level)\} \end{aligned}$$

$$C(X, Y) = \begin{cases} 1 & (X = Y) \\ 0 & (X \neq Y) \end{cases}$$

where

$data[H]$: learning history information of size H

$data[j].Achieve$: the value of attribute "understanding of verification problem" of learning object metadata used in the j-th learning

$data[j].\ LOM \rightarrow XX$: the attribute values of learning object metadata used in the j-th learning (taxon, activity, and level)

Then, the adaptability function (objective function) to be used in the sequencing in this study is given as follows.

Adaptability function

$$\begin{cases} f_{rel}(Cs) = W_{LH}(Cs) \times Relation(Cs) \\ f_{pre}(Cs) = W_{LH}(Cs) \times Presupposition(Cs) \\ f_{dif}(Cs) = W_{LH}(Cs) \times Difficulty(Cs) \\ f_{act}(Cs) = W_{LH}(Cs) \times Activity(Cs) \end{cases}$$

5.5. Genetic operator

When GA is applied to learning assist, the genetic operator should be such that the logical flow and the context of learning, that is, connections of learning, are not destroyed. In other words, the crossover to generate a new individual and the mutation to exchange genes without destroying the character of the excellent individual, are required.

In the learning object sequencing in this study, the crossover procedure, which generates an individual combining two individuals emphasizing the character of the individuals, is realized, based on the sub-tour exchange crossover. The mutation process is realized by exchanging LOM on the individuals, while considering the flow and context of learning. The construction of the genetic operator in this study is described in the following, together with the algorithm.

The genetic operator consists of selection, crossover, mutation, and migration. In particular, crossover and mutation can emphasize the particular evaluation viewpoints (the relations among unit items, the presupposition of unit item, the difficulty of unit item, and the adequateness of learning action). The crossover and mutation which are applied to the "relations among unit items" are described in this paper. For other evaluation viewpoints, similar implementations are applied. The migration is described in Section 5.6.

Selection

The elite preservation and the expectation strategies are used in the selection. As the first step, applying the elite preservation strategy, the individual (Cs) with the highest adaptability in each subset is preserved. Then, the expectation strategy is applied. The expectation of the descendent from each individual is calculated, and the individual is selected according to the expectation.

Crossover

The crossover is essentially based on the sub-tour exchange crossover, which emphasizes the characters of two parent individuals. In other words, a method is used which generates the child individuals while emphasizing the logical flow and context of learning. The procedure to generate child individuals (C, D) from parent individuals (A, B) is as follows.

```
Procedure crossover (relations)
begin
  for i := 1 to size(size of subset) do begin
     parent individual (A) := individual (Cs_i) ∈ individual
     set of generation T ;
     rnd := random variable in [1, size] ;
     parent individual (B) := individual (Cs_rnd) ∈ individual
     set of generation T ;
     if parent individual (A) != parent individual (B) then begin
          Procedure crossover of parent individual (A), (B);
     end;
  end;
  Procedure reconstruction of subset
end{ crossover (relations)};
```

```
Procedure   crossover of parent individual (A), (B)
begin
  rnd := random variable in [0, 1];
  if P_c (crossover rate) ≧ rnd then begin
     for j := 1 to 2 begin
        arbitrary position of parent individual (start) :=
        random variable in [1, L (individual length)] ;
        length (length) of subset (Δ X) := random variable in
        [1, L] ;
        n := 0;
        while R (LOM_{start+n}, LOM_{start+n+1}) ≧ δ
          and n < L
          and start + n + 1 ≦ L do begin
             n := n + 1;
        end;
        Δ X := {LOM_start, ..., LOM_{start+n}};
        child individual (C) := parent individual (B) + Δ X;
        (child individual (D) := parent individual (A) + Δ X;)
     end;
     temporary storage: = parent individual (A, B), child
     individual (C, D) ;
  end;
  else begin
     temporary storage: = parent individual (A, B) × 2;
  end;
end{ crossover of parent individual(A), (B) };
```

$R(LOM_i, LOM_j)$: relation between the value of attribute "taxon" (name of unit item) of i-th LOM and the value of attribute "taxon" of j-th LOM

δ: relation above the specified value (threshold for determining subsequence)

ΔX: subsequence extracted from parent individual

The parent individual $(B/A) + \Delta X$: subsequence (ΔX) is overwritten on the most similar part of the other parent individual. More precisely, it is exchanged with the subsequence (of *length*) of the parent individual, which contains as many unit items related to the attribute value of "taxon" of LOM composing the subsequence (ΔX) as possible.

```
Procedure reconstruction of subset
begin
   for i := 1 to size×G do begin
      rnd := random variable in [1, 2×size] ;
      individual set for replacement :=
         individual (Cs_rnd) ∈ individual set in
         temporary storage;
   end;
   for i := 1 to size×G do begin
      rnd_1 := random variable in [1, size] ;
      rnd_2 := random variable in [1, size×G] ;
      individual (Cs_{rnd_1} ∈ subset before crossover) :=
         individual (Cs_{rnd_2} ∈ individual set for
         replacement) ;
   end;
end{ reconstruction of subset };
```

G :   crossover rate (0,1]

Mutation

In the mutation, LOM on the individuals is replaced, considering the flow and context of learning, of all individuals (by the number *size*). More precisely, the position (i) for replacing LOM is determined based on the "weakness of the relation between unit items." The weakness ($nR(LOM_i)$) is formulated as follows:

$$nR(LOM_i \in \text{individual } (Cs)) \leftarrow 1 - R(LOM_i, LOM_{i+1})$$

The position (i) is determined by the following procedure:

```
Procedure mutation (relations) ~ selection of position (i) ~
begin
  for k := 1 to L(individual length) − 1 do begin
     total := total + nR(LOM_k ∈ individual (Cs));
  end;
```

```
total_0 := 0;
i := 1;
while i < L do begin
total_i := total_{i-1} + nR(LOM_i ∈ individual (Cs))/total;
  if P_m(mutation rate) ≦ total_i then begin
    break;
  end;
  i := i + 1;
end;
end{ mutation (relations) ~ selection of position (i) ~};
```

When the replacement position (i) is determined arbitrarily, LOM_{new} is newly inserted between LOM_i and LOM_{i+1}. LOM_{L+1} is deleted. The new LOM_{new} is determined based on the learning necessity information preset by the learner, by retrieving the learning object metadata from the database and selecting one from the retrieved result using a random function. The reason for deleting LOM_{L+1} when inserting LOM_{new}, not only simply replacing LOM_i, is to avoid the destruction of the connection between LOM_{i-1} and LOM_i.

Terminating condition and selection of optimal solution

The adaptability in the range [0,1] is determined by each adaptability function. The termination condition uses the adaptability of 0.90, not the number of generations, as the decision criterion. When any of the subset satisfies the criterion, which is defined for each subset, the calculation of the computation model (Fig. 3) is terminated. In this approach, the solution is searched, dividing the whole set into multiple subsets. Consequently, if there is a significant difference among the growth of individuals in subsets, the calculation should be continued until all subsets satisfy the criterion.

When, however, the evaluation experiment (1) of Section 6.2.1 is iteratively executed, there is no significant difference in the growth of the individuals. Consequently, the following condition is used. This study employs an optimization technique where multiple Pareto-optimal solutions are derived by a single calculation. Consequently, there must be a framework by which the preferred solution is selected from the derived solution candidates. In this study, the learner selects the preferred solution. The procedure is as follows.

[step 1] The number of displays (Y) of the learning object sequence is defined (learner).

[step 2] The number of solution candidates to be selected from each subset is defined (system).

[step 3] Upper ($Y/4$) solution candidates are selected from each subset, based on the adaptability (system).

[step 4] A preferred solution is selected from Y solution candidates (learner).

5.6. Learning object sequence reflecting intention information

The sequencing in this study is based on the processing in which four evaluation viewpoints are equivalently weighed. Among the learners, however, there can be a learner who weighs more the learning necessity of "learning as many related unit items as possible" or "learning the unit item through various learning activities (actions)." It will then be necessary that the learning object sequence satisfying the requirement be provided to the learner according to such a requirement.

As was described in Section 4, a framework is realized in the proposed method, in which the priority (weight) of the evaluation viewpoint can be modified, and various learning object sequences emphasizing arbitrary evaluation viewpoint can be realized. The interaction module provides four parameters, by which the priorities of the evaluation viewpoints can be modified. The parameter takes the value in Refs. 1 and 5. The learner represents his real-time intention by adjusting the four parameters. In this study, this information is called "intention information" of the learner.

The intention information is reflected on the migration in GA calculation model in the proposed method. The migration is the important manipulation in the distributed GA, in order to maintain the diversity of the whole set and the subsets. The GA parameters that control the migration process are the migration topology (determination of migration destination), the migration interval (execution interval of migration), the migration rate (ratio of individuals to be migrated), and the selection of migrating individual (selection and insertion of individual to be migrated and selection of individual after migration).

The migration rate is the important parameter, in order to maintain the diversity of the whole set and subsets, and to derive a solution of excellent quality. It is shown in the preceding study that the migration rate and the diversity are related as "increase of migration rate" ⇔ "destruction of diversity in the whole set." In other words, when the migration rate of a subset is increased, the character of the migrating subset is propagated to the whole set, due to the fact that a larger number of individuals with the character of the originating subset migrate to other (destination) subsets.

By utilizing the above property, a method is proposed in this study whereby the migration rate is controlled according to the intention information of the learner, so that a large number of learning object sequences are generated to satisfy the evaluation viewpoint, which is weighed more heavily by the learner.

More precisely, the migration rate $P_{mig}(item)$ of the subset, which evaluates the individual from the evaluation viewpoint weighed heavily by the learner, is determined by the following expression.

Migration rate

$$P_{mig}(item) \leftarrow X \times P_{mig\_default}$$

$item$: evaluation viewpoint (integration/connection/difficulty of unit items, connection of learning actions)

X : parameter of intention information of the learner

$X \in \{X_{rel}, X_{pre}, X_{dif}, X_{act}\}$

$P_{mig\_default}$: initial migration rate

By the above mechanism, a large number of individuals migrate from the subset with priority to other subsets, so that the individuals with characters emphasizing the evaluation viewpoint with priority are disseminated over the whole set.

6. System Evaluation and Discussion

This section presents the e-learning system developed in this study, which contains the learning object sequencing function. The result of an evaluation experiment is reported, which was employed to examine the validity and the usefulness of the system.

6.1. System interface

Figure 5 shows the interfaces of the system. The learner registers the learning necessity (2) through UI-①. UI-② gives the result of retrieval, that is, the learning object sequence, which is generated by the learning object sequencing module. As was already discussed, in this study, the optimization technique in the multi-objective optimization problem is applied as the sequencing procedure, which results in multiple optimal solutions. The learner must select the preferred solution (to be used as the learning object sequence in the learning).

As the criterion in the selection, the evaluation score of each evaluation viewpoint for each learning object sequence is presented. Four kinds of evaluation value are presented: “integration of unit items (relations among unit items),” “relation of unit item (presupposition of unit item),” “difficulty of unit item,” and “context of learning action (adequateness of learning action).” The values of the objective functions derived in the computation model are used for those presentations.

Fig. 5. System’s interface.

UI-③ is the screen displaying the detailed information of the learning object sequence selected in UI-②. The values of the attribute information of the learning object metadata composing the learning object sequence are displayed, following the order of learning. UI-④ is the screen where the learning object sequence described in Section 5.6 is corrected. After modifying the respective parameters, and selecting the button “reflection of intention information,” the parameters (intention information) are sent to the interaction module, and the learning object sequence is reconstructed.

UI-⑤ is the screen where the learning object is executed. The learner selects the learning object to execute, using the pop-up menu “learning order,” and proceeds in the learning. When the multi-choice verification problem is presented, the answer must be selected after the learning (before starting the learning of another learning object).

6.2. Evaluation and discussion

This section reports on the evaluation experiment, which was executed in order to examine the usefulness and the validity of the proposed system. The evaluation items are the usefulness of the sequencing by GA and the validity of the generated learning object sequence.

6.2.1. Usefulness of sequencing procedure

There has not been established a quantitative evaluation method for the multi-objective optimization problem using GA. Some methods to provide quantitative evaluation of the multi-objective optimization problem were proposed in preceding studies [6, 7]. In Ref. 6, four evaluation measures are presented: (1) number of individuals, (2) accuracy, (3) covering ratio, and (4) diversity. Among those, however, (2) and (3) are limited to problems for which the true Pareto-optimal solution is known, and (4) is limited to two-objective problems. In Ref. 7, the covering rate in Ref. 6 is extended to problems, for which the true Pareto-optimal solution is unknown, or problems with three or more objectives.

In the learning object sequencing problem considered in this paper, the true Pareto-optimal solution is unknown and there exist four objective functions. Consequently, the number of individuals [6] and the covering rate [7] are used to discuss the results of experiments.

Number of individuals The number of individuals is the value that indicates whether or not the Pareto-optimal solution is obtained.

Covering rate The covering rate is the value that indicates the ratio with which the Pareto-optimal solutions are covered. It is given as

$$C_k = \frac{N_k}{N}$$

where

N_k: number of small regions that contain Pareto-optimal solution

N: number of divisions (number of subsets)

The small region is determined by dividing the interval of the objective function [minimum value, maximum value] based on the Pareto-optimal solution, by the number of partitions. The covering rate (C) for the set of Pareto-optimal solutions is determined as the average of the covering ratio (C_k) of each objective function:

$$C = \frac{\sum_{k=1}^{M} C_k}{M}$$

where M is the number of objective functions.

The evaluation experiment is run using two kinds of parameters (Tables 4 and 5). The first is to see the distribution of Pareto-optimal solutions when the four evaluation viewpoints are equally weighed. The second is to examine the distribution of Pareto-optimal solutions when the objective function "relations among taxons" is given the priority. The second case is especially considered in comparison to the first.

Table 4. Parameter (1)

number of individuals in whole set	200
length of individual	10
crossover rate	0.85
mutation rate	0.05 (P_m in 5.5 correspond to $0.95 (= 1 - 0.05)$
migration interval	5 generations
migration rate (initial value)	0.2
weight of objective function	$f_{rel}(Cs) : f_{pre}(Cs) : f_{dif}(Cs) : f_{act}(Cs) = 1 : 1 : 1 : 1$
migration rate of subset	$= 0.2 : 0.2 : 0.2 : 0.2$

The learning history is reflected, as discussed in Section 5.4, on the learning history information of the user for evaluation experiment, who already used 10 learning objects. The result of evaluation, as well as discussion, is presented next.

Evaluation experiment (1)

In evaluation experiment (1), the termination condition is satisfied by the adaptability (0.92) of the objective function $\{f_{dif}(Cs)\}$ that evaluates the "difficulty of unit item." Figure 6 shows the Pareto-optimal solution, which is obtained by combining the objective function $\{f_{dif}(Cs)\}$ with other objective functions $\{f_{rel}(Cs), f_{pre}(Cs), f_{act}(Cs)\}$, as a two-objective problem. Table 6 shows the number of individuals, the covering ratio, as well as the maximum and minimum values of the Pareto-optimal solution for each objective function.

According to the experimental results, almost half of the individuals in the set are determined as the Pareto-optimal solutions. The rest, however, are the individuals which did not grow to the Pareto-optimal solution or the individuals which overlap with other individuals. The overlap with other individuals is frequently observed in the small region of the interval [0.68, 0.76] of the objective function $\{f_{dif}(Cs)\}$. The covering rate is 0.74. There are small regions in interval [0.76, 0.82] of the objective function $\{f_{dif}(Cs)\}$, which does not contain an individual. In other words, the growth of the individual is retarded on $f_{dif}(Cs) = f_{ref}(Cs), f_{dif}(Cs) = f_{pre}(Cs)$, and $f_{dif}(Cs) = f_{act}(Cs)$.

Table 5. Parameter (2)

migration rate (initial value)	0.2
weight of objective function	$f_{rel}(Cs) : f_{pre}(Cs) : f_{dif}(Cs) : f_{act}(Cs) = 3 : 1 : 1 : 1$
migration rate of subset	$= 0.6 : 0.2 : 0.2 : 0.2$

The number of individuals in the whole set, individual length, crossover rate, mutation rate, and migration interval are the same as in Table 4.

The sharing process is not introduced in the proposed method, which may be the reason for the expansion of the individual in certain intervals, as well as the overlap of individuals among small regions. In the distributed GA, the basic procedure is the local search in each subset. This may have emphasized the solution search weighing more on the particular objective function. In order to derive the solution satisfying multiple objective functions with a good balance, the dependence of the result on GA parameters other than the migration rate that determines the migration effectiveness, should be examined.

Evaluation experiment (2)

In evaluation experiment (2), the terminating condition is satisfied by the adaptability (0.93) of the objective function $\{f_{rel}(Cs)\}$ to evaluate the "relations among unit items." Figure 7 shows the Pareto-optimal solution, which is obtained by combining the objective function $\{f_{ref}(Cs)\}$ with other objective functions $\{f_{pre}(Cs), f_{dif}(Cs), f_{act}(Cs)\}$, as the two-objective problem. Table 7 shows the number of individuals forming the Pareto-optimal solution, the covering rate, as well as the maximum and minimum values of Pareto-optimal solutions for each objective function.

Observing the experimental results, almost half of the individuals are contained in the set of Pareto-optimal solution, as in evaluation experiment (1). The covering rate is 0.67. In this study, the optimization technique to control the migration rate is proposed so that a larger number of Pareto-optimal solutions emphasizing the arbitrarily specified objective function can be derived. So far as the number of individuals is examined, the result is not satisfactory. There are several points, however, that should be considered.

Table 6. Results of experiment (1)

number of individuals		119
covering rate		0.72
maximum and minimum values	$f_{rel}(Cs)$	{0.88, 0,60}
	$f_{pre}(Cs)$	{0.84, 0.61}
	$f_{dif}(Cs)$	{0.92, 0.63}
	$f_{act}(Cs)$	{0.87, 0.59}

One is the diversity of solutions. There is no remarkable difference between the covering rates between evaluation experiment (2) with the priority on an objective function and evaluation experiment (1) equally weighing multiple objective functions. In other words, it seems that the diversity of solutions is not affected greatly by emphasizing a particular objective function.

The other is the maximum and minimum values of each objective function. In the emphasized objective function, the minimum value is higher than in other objective functions. The maximum value, on the other hand, is lower in other objective functions. In other words, the quality of the solution is improved in the subset evaluating $f_{ref}(Cs)$, but is lowered in other subsets. It is also suggested that the interval for each objective function is narrowed. It is suggested from Fig. 7 that the Pareto-optimal solutions are not many in the regions where $f_{pre}(Cs), f_{dif}(Cs), f_{act}(Cs) > f_{ref}(Cs)$.

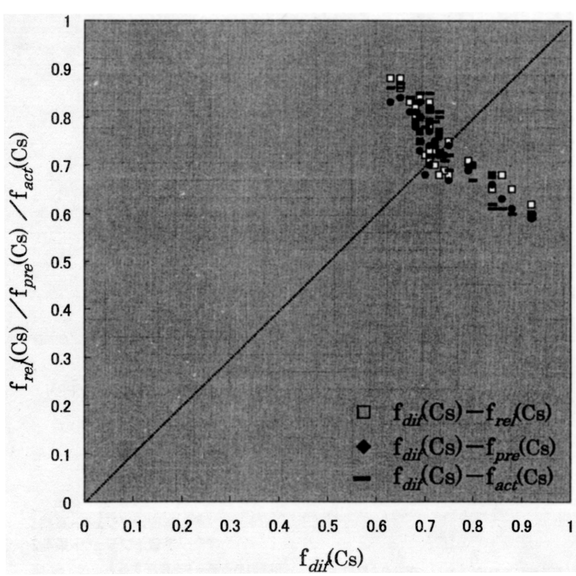


Fig. 6. Pareto solutions (1).

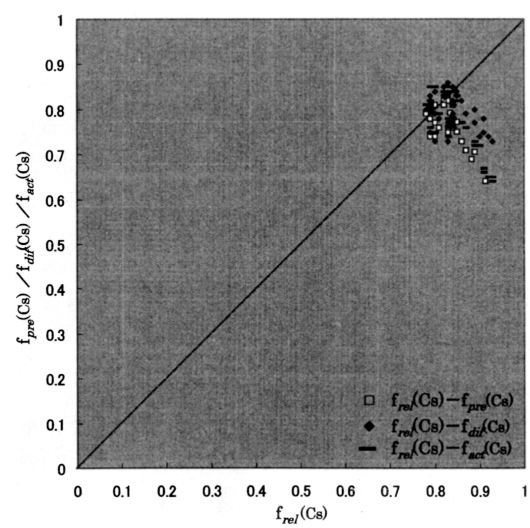


Fig. 7. Pareto solutions (2).

Table 7. Results of experiment (2)

number of individuals		97
covering rate		0.67
maximum and minimum values	$f_{rel}(Cs)$	{0.94, 0,79}
	$f_{pre}(Cs)$	{0.83, 0.64}
	$f_{dif}(Cs)$	{0.86, 0.73}
	$f_{act}(Cs)$	{0.85, 0.64}

The above properties seem to be the reason for the larger number of Pareto-optimal solutions weighing more on the objective function $f_{ref}(Cs)$. This is the result of the situation where a large number of individuals migrate from the subset evaluating the "relations among unit items" to other subsets. Then, the character of the "relations among unit items" is propagated to other subsets, resulting in a situation where the whole set contains individuals with the same character. Compared to the result of evaluation experiment (1), there exist remarkable expansion and overlap of individuals, and it is necessary in the proposed method to improve the selection of individuals in the solution search process.

6.2.2. Validity of learning object sequence

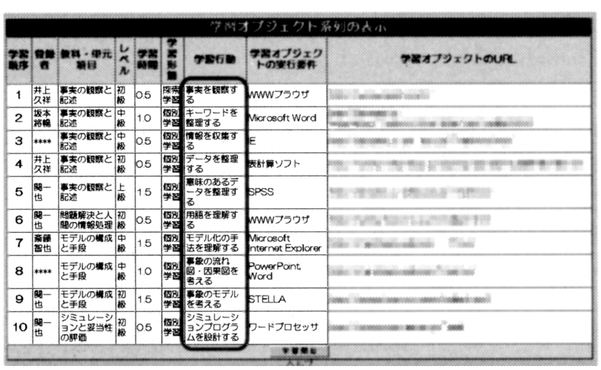
An evaluation experiment was run, in order to examine the validity of the learning object sequence, which is generated by the learning object sequencing procedure in this study.

Evaluation experiment (3)

In evaluation experiment (3), the learning object sequence 1, when the four evaluation viewpoints are equally weighed, and the learning object sequence 2, when the evaluation viewpoint emphasizes the "adequateness of learning action," are compared using an actual example. In the generation of the learning object sequence, Table 2 is used for the learning necessity of the learner, and Table 4 is used for GA parameters. As the intention information of the learner, it is set that $f_{ref}(Cs) : f_{pre}(Cs) : f_{dif}(Cs) : f_{act}(Cs) = 1 : 1 : 1 : 4$.

Comparing 24 learning object sequences, which are generated for each condition, it is observed that the longer subsequence results generally in learning object sequence 2 than in learning object sequence 1, as is shown in the "trace of learning action" in Fig. 10. Figures 8 and 9 show the learning object sequences which clearly indicate the relation to the "learning action."

Figure 10 shows the competence model for achieving the learning goal shown as the learning necessity (Table 2) (i.e., the acquisition of knowledge and skill for collection and organization of information). It is the tracing of the information related to the "learning action" in two learning object sequences (Figs. 8 and 9). It is seen from the experimental results that largely two subsequences are formed. According to the information "learning order" in Fig. 8, {2,



学習オブジェクト系列の表示

学習順序	登録者	教科・単元項目	レベル	学習時間	学習形態	学習行動	学習オブジェクトの実行要件	学習オブジェクトのURL
1	井上久祥	事実の観察と記述	初級	0.5	探索学習	事実を観察する	WWWブラウザ	
2	坂本将暢	事実の観察と記述	中級	1.0	個別学習	キーワードを整理する	Microsoft Word	
3	****	事実の観察と記述	中級	0.5	個別学習	情報を収集する	E	
4	井上久祥	事実の観察と記述	初級	0.5	個別学習	データを整理する	表計算ソフト	
5	関一也	事実の観察と記述	上級	1.5	個別学習	意味のあるデータを整理する	SPSS	
6	関一也	問題解決と人間の情報処理	初級	0.5	個別学習	用語を理解する	WWWブラウザ	
7	斎藤智也	モデルの構成と手段	中級	1.5	個別学習	モデル化の手法を理解する	Microsoft Internet Explorer	
8	****	モデルの構成と手段	中級	1.0	個別学習	事象の流れ図・因果図を考える	PowerPoint, Word	
9	関一也	モデルの構成と手段	初級	1.5	個別学習	事象のモデルを考える	STELLA	
10	関一也	シミュレーションと妥当性の評価	初級	0.5	個別学習	シミュレーションプログラムを設計する	ワードプロセッサ	

Fig. 8. Sequence of learning objects.

学習オブジェクト系列の表示

学習順序	登録者	教科・単元項目	レベル	学習時間	学習形態	学習行動	学習オブジェクトの実行要件	学習オブジェクトのURL
1	*****	問題の分析と解決の手段	初級	0.5	探求学習	用語を理解する	Microsoft Internet Explorer	
2	関一也	問題解決と人間の情報処理	中級	0.5	個別学習	用語を理解する	WWWブラウザ	
3	坂本将暢	モデリング手法	中級	1.5	探求学習	モデル化の手法を理解する	Microsoft Internet Explorer	
4	井上久祥	事実の観察と記述	初級	0.5	探索学習	事実を観察する	WWWブラウザ	
5	井上久祥	事実の観察と記述	初級	0.5	個別学習	データを整理する	表計算ソフト	
6	関一也	事実の観察と記述	上級	1.5	個別学習	意味のあるデータを整理する	SPSS	
7	****	モデルの構成と手段	初級	0.5	個別学習	事象の流れ・因果関係を整理する	PowerPoint	
8	井上久祥	モデルの構成と手段	初級	0.5	グループ学習	事象の流れ図・因果図を考える	電子メール	
9	****	モデルの構成と手段	中級	1.0	個別学習	事象の流れ図・因果図を考える	PowerPoint, Word	
10	関一也	モデルの構成と手段	初級	1.5	個別学習	事象のモデルを考える	STELLA	

Fig. 9. Sequence of learning objects (Competency).

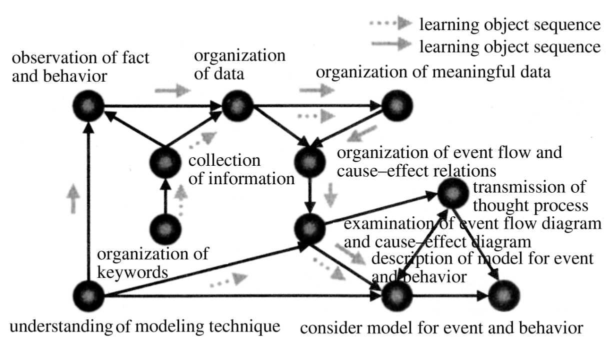


Fig. 10. Traces of learning activity.

Table 8. Comparison of learning object sequences

	learning object sequence (1)	learning object sequence (2)
mean	2.88	4.00
variance	0.70	0.57
t–value	2.83	
significance level	0.013*	

$*p < .05$

3, 4, 5}, {7, 8, 9} are the subsequences. In learning object sequence 2, on the other hand, the learning order continues from 1 to 10 without a break, and there is no integration of learning actions. A relatively long subsequence {3, 4, 5, 6, 7, 8(9), 10}, however, is formed.

Table 8 shows the result of evaluations for the difference in the integration of learning actions between the two learning object sequences, where nine examinees undertook the evaluation without knowing which procedure was used in the generation. Five-stage evaluation score is used in the evaluation (1: integration is very weak, 5: integration is very strong). The both-sided t-test with a significance level of 5% is applied to the evaluation scores for the two learning object sequences, and a significant difference is verified between the two.

By the above examinations, the considered learning object sequencing procedure, in which the intention information of the learner is reflected and a certain objective function is evaluated with emphasis, works adequately for the actual learning object sequencing.

Evaluation experiment (4)

Evaluation experiment (4) examines whether or not there is a difference between the learning object sequence constructed by the teacher (expert) and the learning object sequence constructed by the proposed system. The examinees are 12 graduate students specializing in information science and undergraduate students specializing in education. The material in the experiment is "modeling and simulation techniques." The examinees are given the material for a guidance plan on "modeling and simulation techniques."* The material contains several detailed guidance plans concerning the material in the experiment.

The learning object sequence is constructed with the following constraint.

1. The learning object sequence should be composed of 10 learning objects.

2. The learning object sequence should be constructed so that the learning ends within 10 hours.

3. The learning objects should be arranged in the learning object sequence, considering the parameter information of the object of learning.

The examinees constructed 28 learning object sequences. The system constructed the learning object sequences based on Table 4. Then, 28 learning object sequences are selected. The difference between the learning object sequences is examined by comparing the evaluation values determined by the objective function given in Section 5.4. The result of comparison is tested by the both-sided t-test with a significance level of 5%. Table 9 shows the mean, variance, t-value, and significance probability for the evaluation values in the respective learning object sequence. It is observed from the experimental results that there is no difference between the learning object sequences constructed by the examinees and by the system.

Thus, it is concluded that the sequencing technique considered in this study can generate a learning object sequence that is comparable to the result by the expert.

Table 9. Average and variance of fitness

		$f_{rel}(Cs)$	$f_{pre}(Cs)$	$f_{dif}(Cs)$	$f_{act}(Cs)$
examinee	mean	.84	.69	.85	.71
	variance	.012	.014	.010	.015
system	mean	.78	.75	.76	.77
	variance	.009	.011	.013	.008
t–value		2.19	2.01	3.14	2.01
significance level		.033*	.050*	.003*	.050*

$*p < .05$

7. Conclusion

This paper proposed the learning ecological model for the e-learning environment. A framework to utilize the learning object of the e-learning environment in the learning activity is designed and implemented. More precisely, learning object is managed using the learning object metadata, and the adequate sequencing of the learning objects is considered based on the learning object metadata information, the learning necessity of the learner, the learning history information, and the curriculum information of the object of learning. This paper especially focused on the learning object sequencing technique.

Multiple evaluation viewpoints, not a single viewpoint, are applied in the sequencing technique in this paper. Consequently, the optimization technique in the multi-objective optimization problem should be used in sequencing. In this study, the genetic algorithm is applied in the optimization procedure, trying to derive the solution efficiently. As another point, the interaction mechanism between the learner and the system is needed, in order to reflect better

*http://www.edu-c.pref.miyagi.jp/: subject "information" guiding plan, Miyagi Educ. Training Center (2000).

the intention of the learner in the generation of the learning object sequence.

In other words, a framework that can generate flexibly the learning object sequence is realized, by utilizing both the advantage of the multi-objective GA that can handle directly the multi-objective property of the multi-objective optimization problem, and the advantage of the distributed GA that can execute the genetic operator independently to the divided small subsets. Through the evaluation experiment, the usefulness of the sequencing procedure in this study, as well as the validity of the learning object sequence generated by the sequencing technique, are verified.

In the proposed method, multiple learning object sequences, which are in trade-off relations, are derived. It may happen that the learner has a difficulty in selecting an adequate learning object sequence. A problem remaining for the future is to propose and implement the function that can assist the decision-making (selection of the preferred solution) of the learner.

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