A SCORM/IMS Compliance Online Test and Diagnosis System

Jyh-Cheng Chang, Shao-Chun Li, Alex Chang and Maiga Chang, *Member, IEEE*

***Abstract*—Teachers always want to know how much their students had learned in classes. The most convenient way to discover learning status is 'test'. Each item on a test sheet always contains one or more concepts used to check whether a student really understands or not. Teachers can also find a student's misconceptions out via the concept relations stored in a test sheet. In order to make the diagnosis process simple, teachers always take concept maps as their test development and learning diagnosis tools. This paper implements a SCORM/IMS compliance online test and diagnosis system base on concept maps. In the system, it has more than 5000 members and generates real-time learning report for misconception diagnosis over 500 times monthly. The members are the third-year student at junior high school and come from different counties and cities all over the country. Currently, the system covers 11 courses such as Chinese, English, Physics, History, and Earth Science. It's obviously the system is useful for both teachers and students.**

***Index Terms*—Learning systems, concept map, online testing, misconception, learning diagnosis**

I. Introduction

As a learner engages in learning activities for a while, some misunderstanding will come up spontaneously and these misconceptions will accumulate. The objective of an exam or test is to find out the learner's misconceptions and to catch on to his/her learning status. For distance education systems, learning activities are industrialized and learning contents are programmed.[8] For assessment, researchers [13][16] suggested us to focus on those concepts embedded in test (or more precisely, in a test item). As we all know, even for the same learning materials and test sheet, not two learners catch the same idea and perform the same test results. Only when the knowledge embedded in the test sheet is well analyzed and computerized, it is possible to provide personalized learning services for the learner based on the learning diagnosis of his/her test results.

Manuscript received March 07, 2006.

Jyh-Cheng Chang is with the Department of Information & Computer Engineering, Chung-Yuan Christian University, Chung Li 32023, Taiwan (phone: +886-3-265-4725; fax: +886-3-265-4799; e-mail: eoda@mcsl.ice.cycu.edu.tw).

Shao-Chun Li is with the Department of Information & Computer Engineering, Chung-Yuan Christian University, Chung Li 32023, Taiwan (e-mail: earry@mcsl.ice.cycu.edu.tw).

Alex Chang is with the Department of Information & Computer Engineering, Chung-Yuan Christian University, Chung Li 32023, Taiwan (e-mail: aslada@mcsl.ice.cycu.edu.tw).

Maiga Chang is with the 2 National Science & Technology Program for e-Learning, Chung-Li 32099, Taiwan (e-mail: maiga@ms2.hinet.net; homepage: http://maiga.dnsalias.org).

A. *Related Works*

Concept maps are usually used as teaching tools. On the work of Ausubel in 1978, concept maps are based in large part. [9] In Ausubel's Assimilation Theory, when learning is occurs in the context of the learner's previous knowledge, concept map becomes meaningful. [14][15] In order to make learning to be meaningful, the learner must try to link new information to existing knowledge structures that are associated to the new knowledge.

Meyer (1985) conducted an extensive research which showed that verbal signals in text can be used by the writer to communicate propositional knowledge at different levels of details. [3] Ausubel believed that concepts are defined and described via propositions, and propositions are used for describing the relations between two concepts.

B. *Outline of this Paper*

This paper proposed a mechanism to diagnose the answer sheet according to the hierarchical concepts embedded in the test sheet. Some necessary backgrounds of concept map and concept hierarchy for analyzing test items and answer sheets are surveyed in Section 2. Section 3 will designs embedded concept matrices in order to transform wrong answers to concept errors inside the student's mind. Furthermore, Section 4 develops two algorithms for diagnosing the misconceptions: one uses concept thresholds to determine misconceptions directly and the other minimizes the errors. In order to verify the mechanism which is proposed by this paper, a real learning system based on the international e-learning standards IMS (which is short for the Instructional Management Systems) and SCORM, is used as the platform. [1] The system offers on-line testing function; therefore, the test sheet and the real-time learning diagnosis are able to prove and integrate to do the experiment. The details of the experiment are described in Section 5. Section 6 make a conclusion and discusses what can be do next.

II. Learning Diagnosis Problem

A. Concept Hierarchy

Pedagogically, *concept maps* help teachers clear what students might either learn on or think in. A *concept map* is also a visual road map to represent meaningful relationships between concepts in the form of propositions. [13] A *concept*, denoted as $c_i \in \boldsymbol{C}$, is an atomic element of knowledge pieces, e.g. flower, grass and tree. As in *propositional semantic network*, any n-term proposition might be illustrated by a series of linking *relations* with just two concepts. [20] A *relation*, symbolized as $r_k \in \underline{R}$ (where r: A Kind of Relation), is usually used to illustrate the relationships among concepts. And the concept c_i is defined and confined via its *propositions* such as $prop(r_k(c_i,c_j))$, which describe those relationships between associated concepts. Therefore, a concept map endows its concepts with a set of concept meanings embedded in propositions schematically.

Following the networking technique [7], the concept relations are classified [14] into three categories: *hierarchical structure* with part-of relations ($\boldsymbol{r_{PART\text{-}OF}}$) and type-of ($\boldsymbol{r_{TYPE\text{-}OF}}$) relations; *linkage structure* with link-to relation; and, *clustering structure* with analogical-to, characteristic-of and evidence-of relations. [23] The first two kinds of relations ($r_k \in \boldsymbol{R} \subseteq \boldsymbol{r_{PART\text{-}OF}} \cup \boldsymbol{r_{TYPE\text{-}OF}}$) illustrate the inheritance and containment relationships between the concept elements, and can forms *concept hierarchy* $\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{r_{PART\text{-}OF}} \cup \boldsymbol{r_{TYPE\text{-}OF}})$.

Concept hierarchy depicts the main skeleton of a concept map, in which the most general concept is located in highest level; whereas, the most specific concept is located in lowest level. [11] Fig. 1 shows an example concept hierarchy of motion theory in physics $\boldsymbol{CH_{Motion}}(\boldsymbol{C_{Motion}}, \boldsymbol{R})$ of motions, where $\boldsymbol{C_{Motion}}$ = { Rectilinear motion (RL), Uniform Velocity motion (UV), Non-uniform Velocity motion (NV), Uniform Acceleration motion (UA), Free-Falling motion (FF), Throw-Up motion (TU)}. Moreover, the number of elements in the concept set $\boldsymbol{C}$ is the length of the concept hierarchy, e.g. $length(\boldsymbol{C_{Motion}}) = 6$.

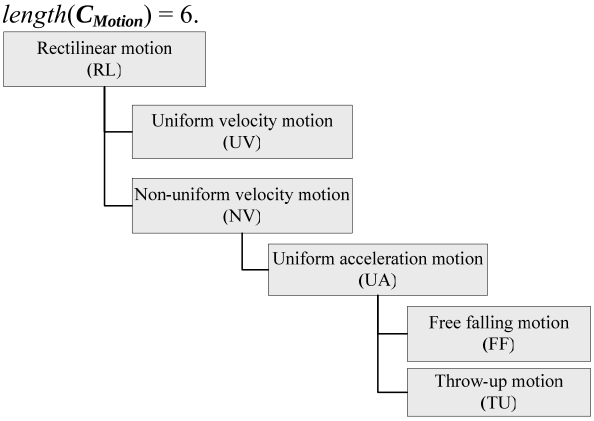

Fig. 1. Concept hierarchy of motion theory in physics.

B. Propositions and Test Items

As we know already, test items can be classified into two categories: [17]

1) *Supply types*: The candidate supplies a segment of answer a^* for the question $prop(x)$,

a) **Short answer:**

e.g. [$prop(x)$,a^*]

= ["What is the name of the author of Moby Dick?", "Herman Melville"].

b) **Completion:**

e.g. [$prop(x)$,a^*]

= ["Lines on a weather map joining points with the same barometric pressure are called _______", "isobars"].

2) *Selection types*: The candidate selects a correct answer x^* from the given alternatives.

a) **True-false or alternative response:**

e.g. [$prop(x)$,a^*]

= ["A virus is the smallest known organism.", "T"].

b) **Multiple-choice:**

e.g. [$prop(x)$,a^*]

= ["A car goes somewhere in the speed of 10m/s and comes back in 15m/s. What is its average speed (m/s)? (A)12.5 (B)5 (C)12 (D)25", "C"].

c) **Matching:**

e.g. [$prop(x)$,a^*]

= ["1.And, 2.Dog, 3.Jump, 4.She, 5.Quickly: (A)Adjective. (B)Adverb. (C)Conjunction. (D)Noun. (E)Preposition. (F) Pronoun. (G)Verb.", "CDGFB"].

Before a gnosis mechanism can be designed to discover the student's mental model from their answer sheets. In general, assertions in the form of declarative sentences that possess values of either true or false, but not both, are called *propositions* (or *statements*), $prop_j$. [25] A sentence may involve a *variable* or an *unknown*, if there is a variable or an unknown x, exist in a sentence true or false until a value of x is assigned. Then, this sentence could be written as $prop(x)$ and could not necessary to be. The sentence becomes a proposition when its variables are replaced by certain allowable choices.

For a sentence $prop(x)$, the sentence is called a question when it has the unknown variable x. Furthermore, an *answer* a^* will make $prop(a^*)$ true. Hence, a *test item* could be denoted as $t(prop(x)) = [prop(x), a^*]$. Different item-types take different advantages. [17] The learning diagnosis algorithm in this paper can be applied to both of two.

C. The Problem

An items bank Q has lots of items, that is, Q is constructed from a set of $t(prop(x))$, Q={ $t_n(prop(x)) = [prop(x), a^*]$, n :the numbers in the items bank} . When doing a test, a *test sheet* is needed. A test sheet is composed of a series of items from items bank, i.e. $\mathbf{q} \in Q$ and $\mathbf{q}$ = [$prop_j(c_i, \ldots x)$: j = 1, 2, …, $size(\mathbf{q})$], where c_i is the concept which is embedded in propositions. Correspondingly, an *answer sheet* $\mathbf{a}^* \in \underline{Q}$ and $\mathbf{a}^*$ = [a_j^*: j = 1, 2, …, $size(\mathbf{q})$]. [28]

Following the previous physics example of $\boldsymbol{CH_{Motion}}(\boldsymbol{C_{Motion}}$,

R) and $t_{Motion}(prop_{Motion}(x))$, we can have an example test sheet of size 5, $\mathbf{q}_{\text{Motion}}$ = [$prop_{M1}(x_1)$, $prop_{M2}(x_2)$, $prop_{M3}(x_3)$, $prop_{M4}(x_4)$, $prop_{M5}(x_5)$], where

1) $prop_{M1}(x_2)$
   = "The velocity of a car go to the destination is 10m/s and its return velocity is 15m/s. What was the magnitude of its average velocity? (m/s) (A)12.5 (B)5 (C)12 (D)25",
2) $prop_{M2}(x_2)$
   = "Throw up a ball vertically. During the up-and-down process, the direction of its acceleration is (A) consistent with motion's direction. (B) contrary to motion's direction. (C) up. (D) down.",
3) $prop_{M3}(x_3)$
   = "A uniform velocity motion (A) must be a parabolic motion. (B) must be rectilinear. (C) is a rectilinear or parabolic motion. (D) is a horizontal motion.",
4) $prop_{M4}(x_4)$
   = "Which motion in the following must be rectilinear? (A) uniform acceleration motion. (B) uniform velocity motion. (C) uniform speed motion. (D) non-uniform acceleration motion.", and
5) $prop_{M5}(x_5)$
   = "For a free-falling motion, the mass of A is twice of that of B, then the acceleration of A is how many times of that of B? (A) 2. (B) 1/2. (C) 4. (D) 1.";

and the corresponding standard answer sheet

$\mathbf{a}_{\text{Motion}}^{*}$
= [a_{M1}*, a_{M2}*, a_{M3}*, a_{M4}*, a_{M5}*]
= ["C", "A", "B", "A", "C"].

After a test, a *learner* u_k will deliver his/her *answer sheet* as $\mathbf{a}(u_k)$ = [$a_j(u_k)$: j=1,2,…], which is possibly used to determined his/her *misconception* $\Delta\boldsymbol{c}(u_k)$. Therefore, the problem which is this paper trying to solve will be:

Problem (Problem of learning diagnosis): Given a concept hierarchy ***CH***(***C***, ***R***), a test sheet $\mathbf{q}$ = [$prop_j(c_i,\ldots x)$: j=1,2,…] and its *standard answer sheet* $\mathbf{a}^*$ = [a_j*: j=1,2,…]. Let a learner u_k take this test and return his/her answer set $\mathbf{a}(u_k)$. Then the objective of our learning diagnosis problem is to find the learner's misconception set $\Delta\boldsymbol{c}(u_k) \subseteq \boldsymbol{C}$.

III. Answer Sheet Analysis

A. Coding of Concepts

Since for those relations in a concept hierarchy ***CH***(***C***, ***R***), $\boldsymbol{R} \subseteq \boldsymbol{r}_{PART\text{-}OF} \cup \boldsymbol{r}_{TYPE\text{-}OF}$ is a partial ordering. (Davey and Priestley, 1990) There are some properties in CH(*C*,*R*).

1. *Concept intension* (*successor*),
   $intension(c_i) = \{c_j: c_i\ r_k\ c_j\}$
2. *Concept extension* (*predecessor*),
   $extension(c_i) = \{c_j: c_j\ r_k\ c_i\}$
3. *Concpt sibling*,
   $sibling(c_i) = \{c_j: extension(c_i) = extension(c_j)\}$
4. *Concpt descendant,*
   $descendant(c_i) = \{c_j: c_i\ r_k\ c_j$ or $descendant(c_i)\ r_k\ c_j\}$
5. *Concpt ascendant,*
   $ascendant(c_i) = \{c_j: c_j\ r_k\ c_i$ or $c_j\ r_k\ ascendant(c_i)\}$

Thus for this concept hierarchy, the *root* (*minimum*) $min(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) = \{c_i$: there is no $c_j \in \boldsymbol{C}$, $c_i\ r_k\ c_j\}$ includes the deepest (maybe more than one) concept(s) For the example in Fig. 1:

1. *intension*(UA) = {FF, TU}
2.

$_{Motion}(\boldsymbol{C}_{Motion}, \boldsymbol{R})) = \{\text{RL}\}$.

A concept hierarchy is a lattice, which means each concept may have more than one predecessor. To simplify the following derivation, Assumption 1 is adopted.

Assumption 1 (Single Inheritance/Containment Assumption): In the designated concept hierarchy ***CH***(***C***, ***R***), each non-root concept possesses only one (unique) predecessor.

With such assumption, a concept hierarchy right becomes a *concept tree*, in which more measures can be defined and the coding of concepts also becomes much simpler.

This assumption makes each concept node in a concept tree own a unique value, called

$level(c_i)$
= 1, c_i is the root; (1A)
= $max\{level(c_{i1}): c_{i1}\ r_k\ c_i,\ r_k \in \boldsymbol{R}\} + 1$, otherwise. (1B)

As a result, the *height* k determined as $height(\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R})) = level(max\{\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R})\}) - level(\min\{\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R})\}) + 1$.

For the previous example,

$level(\boldsymbol{C}_{Motion})$
= [1, 2, 2, 3, 4, 4]

and

$height(\boldsymbol{CH}_{Motion}(\boldsymbol{C}_{Motion}, \boldsymbol{R}))$
= 4.

Some apparent properties of (1) and height in a concept hierarchy are listed in the following lemma without proof.

Lemma 1: **(A)** $level(intension(c_i)) = level(c_i) + 1$, and $level(extension(c_i)) = level(c_i) - 1$. **(B)** $level(sibling(c_i)) = level(c_i)$. **(C)** $level(min(c_i)) = 1$, and $level(max(c_i)) \le height(\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R}))$.

With these measures (length, level and height), all the concepts can be coded in a $length(\boldsymbol{C}) \times height(\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R}))$ matrix, called *Concept Hierarchy code* (***CHcode***) (or simply $\boldsymbol{CHcode}(\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R}))$ = [$\boldsymbol{CHcode}(c_i)$]) $\in \{0,1\}^{length(\boldsymbol{C}) \times height(\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R}))}$, with all rows as corresponding *concept codes* in pre-order tracing:

$\boldsymbol{CHcode}(c_i)$
= [1, 0, …, 0]$^{\mathrm{T}}$, if c_i is a root; (2A)
= $\boldsymbol{CHcode}(c_{i-1}) \cup [\ 1\ ]$ (one more bit 1 to the tail) , if $c_i = intension(c_{i-1})$; (2B)
= $\boldsymbol{CHcode}(c_j)$, if $c_j = sibling(c_i)$ and $j < i$. (2C)

With (2), the concept hierarchy code of Fig. 1 can be found out as Table I.

TABLE I
CONCEPT HIERARCHY CODE (CHCODE)

Concepts\levels	1	2	3	4
Rectilinear motion (RL)	1			
Uniform Velocity motion (UV)	1	1		
Non-uniform Velocity motion (NV)	1	1		
Uniform Acceleration motion (UA)	1	1	1	
Free-Falling motion (FF)	1	1	1	1
Throw-Up motion (TU)	1	1	1	1

Although (2) gives a compact coding of concept hierarchy, the use of $\boldsymbol{CHcode}(\boldsymbol{C})$ in learning diagnosis is not so efficient. In many derivations, a more direct representation of $length(\boldsymbol{C})\times length(\boldsymbol{C})$ matrix, called *concept hierarchy matrix* ($\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) \in \{0,1\}^{length(\mathbf{C})\times length(\mathbf{C})}$) , to illustrate the relationships among concepts will work better:

$\boldsymbol{CHM}(c_i,c_j)$

$= 1$, if $c_i \in ascendant(c_j)$; (3A)

$= 0$, otherwise. (3B)

Table II shows a **CHM** example for the concept hierarchy in Fig. 1. Obviously, the transformation between **CHcode** and **CHM** is one-to-one. The algorithm will be shown in next section.

TABLE II
CONCEPT HIERARCHY MATRIX (CHM)

CHM	RL	UV	NV	UA	FF	TU
RL		1	1	1	1	1
UV						
NV				1	1	1
UA					1	1
FF						
TU						

B. Embedded Concepts in a Test Sheet

Applying the above concept coding to a test item, we are able to quantify the embedded concepts. For a test item $t(prop(c_i,\ldots x)) = [prop(c_i,\ldots x), a^*]$, the *embedded concept* can be described as $\boldsymbol{EC}(t(prop(c_i,\ldots x))) \in \{0,1\}^{length(\mathbf{C})}$. For example, $\boldsymbol{EC}(t_{M2}(prop_{M2}(c_i,\ldots x))) = [\,0\;0\;1\;0\;1\;1\,]^T$, where three bit-1's indicate that $t_{CE2}(\cdot)$ includes concepts "NV", "FF" and "TU". Generally, the *embedded concept matrix* (ECM) for a test sheet $\mathbf{q} = [\,prop_j(c_i,\ldots x)]$ is $\boldsymbol{ECM}(\mathbf{q}) = [\,\boldsymbol{EC}(t(prop_j(c_i,\ldots x)))\,] \in \{0,1\}^{length(\mathbf{C})\times size(\mathbf{q})}$. By the way, the counts of all concepts can be accumulated as a *concept distribution* (CD) of this test sheet **q**:

$\boldsymbol{CD(q)}$

$= \Sigma_j \boldsymbol{ECM(q)}$

$= \boldsymbol{ECM(q)}\cdot\mathbf{1}$. (4)

An example matrix is shown in Table III and the last column is its concept distribution.

TABLE III
EMBEDDED CONCEPT MATRIX

Concepts\items	q_{M1}	q_{M2}	q_{M3}	q_{M4}	q_{M5}	CD
RL				1	1	2
UV			1			1
NV	1	1				2
UA				1		1
FF		1			1	2
TU		1				1

Incorporating hierarchical relations with ***ECM***, another *Cumulative Embedded Concept Matrix* (CECM) is proposed as:

$\boldsymbol{CECM}(\mathbf{q})$

$= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C}))\,)\cdot\boldsymbol{ECM}(\mathbf{q})$, (5)

where $\boldsymbol{I}(length(\boldsymbol{C}))$ is the $length(\boldsymbol{C})\times length(\boldsymbol{C})$ identity matrix.

TABLE IV
CECM AND CONCEPT DISTRIBUTION

CECM	q_{M1}	q_{M2}	q_{M3}	q_{M4}	q_{M5}	CCD
RL	1	3	1	2	2	9
UV			1			1
NV	1	3		1	1	6
UA		2		1	1	4
FF		1			1	2
TU		1				1

For the example in Table IV, both the concepts "UA" and "RL" appear in $\mathbf{q}_{M4}$ once then get the values 1's. The first concept (UA) is related to concepts NV and RL, thus makes concept NV has the value 1 and concept RL has the value 2 at the same time.

As ***CECM*** is obtained, the *cumulative concept distribution* (CCD), or called *conceptrum*, of this test sheet **q** can be found:

$\boldsymbol{CCD(q)}$

$= \Sigma_j \boldsymbol{CECM(q)}$

$= \boldsymbol{CECM(q)}\cdot\mathbf{1}$

$= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C}))\,)\cdot\boldsymbol{CD}(\mathbf{q})$, (6)

where $\mathbf{1} = [1, 1, \ldots, 1]$ a $size(\boldsymbol{q})$ all-one vector. The last column in Table V shows the calculated values of conceptrum. As probability distribution, a conceptrum represents the distribution of concepts within a test sheet and can be graphically illustrated as Fig. 2. As shown, such distribution is extraordinarily non-uniform. One kind of normalization comes from the viewpoint. A *normalized cumulative embedded concept matrix* (NCECM) is defined as:

$\boldsymbol{NCECM}(\mathbf{q})$

$= \boldsymbol{CECM}(\mathbf{q})\;./\;\boldsymbol{CCD(q)}$, (7)

in which $\mathbf{X}./\mathbf{y}$ means a row-wise division of **X** by the corresponding values in **y**. With $\boldsymbol{CCD}(\mathbf{q}_M)$ in Fig. 2, (7) can transform $\boldsymbol{CECM}(\mathbf{q}_M)$ to $\boldsymbol{NCECM}(\mathbf{q}_M)$ in Table V.

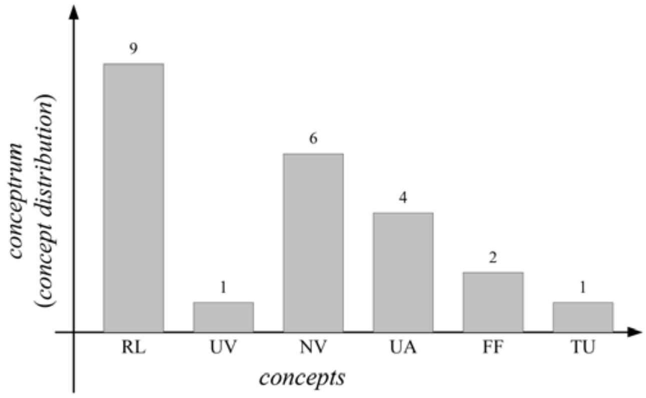

Fig. 2. Conceptrum

TABLE V
NORMALIZED CUMULATIVE EMBEDDED CONCEPT MATRIX

Concepts\ NCECM\ items	$\mathbf{q}_{M1}$	$\mathbf{q}_{M2}$	$\mathbf{q}_{M3}$	$\mathbf{q}_{M4}$	$\mathbf{q}_{M5}$
Rectilinear motion (RL)	1/9	3/9	1/9	2/9	2/9
Uniform Vel. motion (UV)			1		
Non-uniform Vel. motion	1/6	3/6		1/6	1/6
Uniform Acc. motion (UA)		2/4		1/4	1/4
Free-Falling motion (FF)		1/2			1/2
Throw-Up motion (TU)		1/2			

C. From Answer Sheet to Misconceptions

After testing, the answer sheet of learner u_k is recorded directly as $\mathbf{a}(u_k) = [\ a_j(u_k)\text{: } j = 1, 2, \ldots, size(\mathbf{q})\ ]$, which can be scored only by the producer himself/herself. Here, we use general comparison operators to indicate the *erroneous answers* of learner u_k: $\Delta\mathbf{a}(u_k) = [\ a_j(u_k) \neq a_j^*\text{: } j = 1, 2, \ldots, size(\mathbf{q})\ ]$. For example, a learner u_1 = "Arthur" gives an answer sheet $\mathbf{a}_{\text{Motion}}(u_1\text{="Arthur"})$ = ["C", "B", "B", "D", "C"], then gets a scoring $\Delta\mathbf{a}_{\text{Motion}}(u_1) = [\ 0, 1, 0, 1, 0\ ]$.

Now, the erroneous answers $\Delta\mathbf{a}(u_k)$ can be transformed from test item space into concept space through the above-mentioned $\boldsymbol{ECM}(\mathbf{q})/\boldsymbol{CECM}(\mathbf{q})/\boldsymbol{NCECM}(\mathbf{q})$ function and get the corresponding *concept error* $\Delta\boldsymbol{C}(u_k)$:

$$\Delta\boldsymbol{C}(u_k) = \boldsymbol{ECM}(\mathbf{q}) \cdot \Delta\mathbf{a}(u_k), \tag{8}$$

cumulative concept error $\Delta\boldsymbol{C}^{\boldsymbol{C}}(u_k)$:

$$\Delta\boldsymbol{C}^{\boldsymbol{C}}(u_k) = \boldsymbol{CECM}(\mathbf{q})\cdot\Delta\mathbf{a}(u_k) = (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C})))\cdot\Delta\boldsymbol{C}(u_k), \tag{9}$$

and *normalized concept error* $\Delta\boldsymbol{C}^{\boldsymbol{N}}(u_k)$:

$$\Delta\boldsymbol{C}^{\boldsymbol{N}}(u_k) = \boldsymbol{NCECM}(\mathbf{q})\cdot\Delta\mathbf{a}(u_k). \tag{10}$$

In other words, the concept errors (and normalized concept errors, respectively) sum up all the (normalized) embedded concepts of the erroneous items. Since all rows in $\boldsymbol{NCECM}(\mathbf{q})$ have been normalized, their range are also constrained to [0,1], as the following lemma shown.

Lemma 2: (A) $\boldsymbol{NCECM}(\mathbf{q})\cdot\mathbf{1}_{size(\mathbf{q})} = \mathbf{1}_{length(\boldsymbol{C})}$. **(B)** $\boldsymbol{NCECM}(\mathbf{q})\cdot\Delta\mathbf{a} \leq \mathbf{1}$, $\forall\Delta\mathbf{a}\in \{0,1\}^{size(\mathbf{q})}$.

Proof:

(A) $\boldsymbol{NCECM}(\mathbf{q})\cdot\mathbf{1}_{size(\mathbf{q})}$
$= \Sigma_j \boldsymbol{NCECM}(\boldsymbol{q})$
$= \mathbf{1}_{length(\boldsymbol{C})}$ $\square$

(B) Because of
$\Delta\mathbf{a} \in \{0,1\}^{size(\mathbf{q})} \leq \mathbf{1}_{size(\mathbf{q})}$
So that,
$\boldsymbol{NCECM}(\mathbf{q})\cdot\Delta\mathbf{a}$
$= \Sigma_j \boldsymbol{NCECM}(\boldsymbol{q}) \leq \mathbf{1}$ $\square$

For example,

$\Delta\boldsymbol{C}_{\text{Motion}}(u_1)$
$= \boldsymbol{ECM}(\mathbf{q}_{\text{Motion}})\cdot\Delta\mathbf{a}_{\text{Motion}}(u_1)$
$= [\ 0, 0, 1, 0, 1, 1\ ] + [\ 1, 0, 0, 1, 0, 0\ ]$
$= [\ 1, 0, 1, 1, 1, 1\ ]$

and

$\Delta\boldsymbol{C}^{\boldsymbol{C}}_{\text{Motion}}(u_1)$
$= \boldsymbol{CECM}(\mathbf{q}_{\text{Motion}})\cdot\Delta\mathbf{a}_{\text{Motion}}(u_1)$
$= [\ 3, 0, 3, 2, 1, 1\ ] + [\ 2, 0, 1, 1, 0, 0\ ]$
$= [\ 5, 0, 4, 3, 1, 1\ ]$.

Also,

$\Delta\boldsymbol{C}^{\boldsymbol{N}}_{\text{Motion}}(u_1)$
$= \boldsymbol{NCECM}(\mathbf{q}_{\text{Motion}})\cdot\Delta\mathbf{a}_{\text{Motion}}(u_1)$
$= [\ 3/9, 0, 3/6, 2/4, 1/2, 1/1\ ] + [\ 2/9, 0, 1/6, 1/4, 0, 0\ ]$
$= [\ 5/9, 0, 4/6, 3/4, 1/2, 1\ ]$
$= [\ 0.55, 0, 0.66, 0.75, 0.5, 1\ ]$.

With the above definitions, it is possible to approach Problem 1. In the following, two algorithms are designed for diagnosing of the misconception of a learner: the first one finds significant misconceptions in (10) directly and the second one determines "optimal" misconceptions in (8) in the sense of possessing the least errors.

IV. ALGORITHMS DESIGN OF LEARNING DIAGNOSIS

A. Algorithm for CHcode to CHM

As mentioned in section 3, there is an algorithm for CHcode to CHM:

Algorithm 1 (for transforming CHcode to CHM): Given a $\{0,1\}^{length(\boldsymbol{C})\times height(\boldsymbol{CH}(\mathrm{C},\boldsymbol{R}))}$ matrix $\boldsymbol{CHcode}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$, to find its corresponding concept hierarchy matrix $\boldsymbol{CHM}\in \{0,1\}^{length(\boldsymbol{C})\times length(\boldsymbol{C})}$.

```
CHM = 0_{length(C)×length(C)} initially.
for i = 1 to length(C) {
    for j = 1 to level(c_i)-1 {
        CHM(ascendant(c_i), c_i) = 1
    }
}
```

B. Naïve Algorithm for Learning Diagnosis

The so-called *Naïve algorithm* directly uses *normalized concept error* $\Delta\boldsymbol{C}^{\boldsymbol{N}}(u_k)$ in (10) derived from normalized ***NCECM*** in (7). During the diagnosis process, one parameter *concept threshold* (more exactly, *misconception threshold*) $\sigma \in [0,1]$ (with default value 0.5) is used to determine the significance of $\Delta C_i^{\boldsymbol{N}}(u_k)$. At learning diagnosis, a student's

(u_k's) concept C_i is called *significant misconception* if $\Delta C_i^N(u_k) \geq \sigma$ then chosen into misconception set $\Delta C(u_k)$. Practically, the misconception thresholds for different concepts may be different and can be experimentally altered by pedagogical experts.

However, the whole story is much more complex. When a parent concept and a child concept are greater than threshold at the same time, the child concept can locate a more specific concept range. When one parent concept and almost all its children concepts are significant, the adoption one parent concept owns a more concise representation (though more general). Therefore, even the basic idea of our method is to compare the normalized concept error $\Delta\boldsymbol{C}^N(u_k)$ with threshold σ, the resultant significant misconceptions still need elaborate adjustments, as the following algorithm stated.

Algorithm 2 (Naïve algorithm for learning diagnosis): Given a concept hierarchy $\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})$, a test sheet $\mathbf{q} = [\, t(prop_j(c_i, ...x))\,]$ and a standard answer sheet $\mathbf{a}^* = [\, a_j^*]$ with embedded concepts $\boldsymbol{ECM}(\mathbf{q}) = [\, \boldsymbol{EC}(t(prop_j(c_i, ...x)))\,]$. Set the misconception threshold σ. For a learner Ψ_k with an answer set $\mathbf{a}(u_k)$, to find his/her misconceptions set $\Delta C(u_k) \subseteq \boldsymbol{C}$.

1) Determine $\boldsymbol{CHcode}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ and $\boldsymbol{CHM}(\boldsymbol{C})$ through Algorithm 1.

2) Find $\boldsymbol{CECM}(\mathbf{q})$, $\boldsymbol{CD}(\mathbf{q})$ and $\boldsymbol{ECECM}(\mathbf{q})$ from (4), (5) and (7) in succession.

3) For the given answer set $\mathbf{a}(u_k)$, calculate $\Delta\mathbf{a}(u_k)$ then $\Delta\boldsymbol{C}^N(u_k)$ in (10).

4) Set the misconception set $\Delta C(u_k) = \{c_i: \Delta c_i^N(u_k) \geq \sigma\}$.

5) Perform the following checks for all $c_i \in \Delta C(u_k)$ to adjust the set $\Delta C(u_k)$.

- **5A)** if $c_i \in term(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$, then $c_i \in \Delta C(u_k)$. (**Rule 1:** if c_i is a terminal concept, then c_i is chosen as a misconception.)
- **5B)** if $c_i \notin term(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ but $\exists! c_{i1} = intention(c_i)$, $c_{i1} \in \Delta C(u_k)$, then $\Delta C(u_k) = \Delta C(u_k) \setminus \{c_i\}$. (**Rule 2**: if c_i is not a terminal concept, but c_i has only a single sub-concept as misconception, then c_i is not a misconception.)
- **5C)** if $c_i \notin term(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ but $\forall c_{i1} \in intention(c_i)$ and $length(extention(c_i)) > 1$, $c_{i1} \in \Delta C(u_k)$, then $c_i \in \Delta C(u_k)$ and $\Delta C(u_k) = \Delta C(u_k) \setminus intention(c_i)$. (**Rule 3:** if c_i is not a terminal concept, but c_i has more than one sub-concept and all these sub-concepts as misconceptions, then c_i is a misconception and its sub-concepts are all deleted from the misconception set.)
- **5D)** if $c_i \notin term(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ but $\exists c_{i1} \in intention(c_i)$ and $length(intention(c_i)) > 1$, $c_{i1} \notin \Delta C(u_k)$, then $\Delta C(u_k) = \Delta C(u_k) \setminus \{c_i\}$. (**Rule 4**: if c_i is not a terminal concept, but c_i has more than one sub-concept and not all these sub-concepts are misconceptions, then c_i is not a misconception.)

For the above example of concept hierarchy in Fig. 1 and $\Delta C_i^N(u_1) = [\, 0.55, 0, 0.66, 0.75, 0.5, 1\,]$ with a unified threshold $\sigma = 0.5$. Though there are five concepts (RL, NV, UA, FF, TU) are all significant misconceptions, Algorithm 2 adopts UA, and rejects FF and TU (by Rule 3). NV is rejected also (by Rule 2). Even RL is more significant; it still does not be selected as a misconception (by Rule 4). Finally, the resultant misconceptions set is $\Delta C(u_1) = \{\text{ UA }\}$.

C. Types of Diagnosis Errors

Though Algorithm 2 provides a solution for Problem 1, such solution still leaves much room to be improved. Firstly, the use of misconception threshold is too subjective, since each user may define his/her own value of threshold, not to mention that the thresholds for different concepts may be set different. Such difference makes everybody get different learning diagnosis report for the same user. Moreover, the errors for classifying concepts into misconceptions or not can be estimated more precisely. With such estimation, it is possible to get an "optimal" solution of learning diagnosis, where the optimality is in the sense of minimizing the *misconception classification errors*.

As derived in (8), erroneous answers $\Delta\mathbf{a}(u_k)$ will induce $\Delta\boldsymbol{C}(u_k)$. With this datum, no matter whether a concept c_i is classified into a correct concept or a misconception, one of two kinds of errors always happens. By the idea of hypothesis testing in statistics and mapping misconception to the designated null hypothesis, we can define two types of errors in similar ways:

type I error

$$\alpha_i(u_k) = \Delta C_i(u_k), \text{ if } C_i \in \boldsymbol{C} \setminus \Delta\boldsymbol{C}(u_k) \tag{11A}$$

(i.e. C_i is not a misconception), and

type II error

$$\beta_i(u_k) = \boldsymbol{CD}(\boldsymbol{q})_i - \Delta C_i(u_k), \text{ if } C_i \in \Delta\boldsymbol{C}(u_k)\,. \tag{11B}$$

(i.e. C_i is a misconception)

Note that different from those definitions in statistics, these errors are defined by counting the occurrences of concepts in concept errors, thus are integers, not values between [0, 1]. Collecting all the elements α_i and β_i, we can have more formal definitions:

$$\boldsymbol{\alpha}(u_k) = \Delta\boldsymbol{C}(u_k)$$

and

$$\boldsymbol{\beta}(u_k) = \boldsymbol{CD}(\boldsymbol{q}) - \Delta\boldsymbol{C}(u_k).$$

For the previous example of $\Delta\mathbf{a}_M(u_1) = [\, 0, 1, 0, 1, 0\,]$,

$$\boldsymbol{\alpha}_M(u_1) = \Delta\boldsymbol{C}_M(\Psi_1) = [\, 1, 0, 1, 1, 1, 1\,]$$

and

$$\boldsymbol{\beta}_M(u_1) = \boldsymbol{CD}(\mathbf{q}_M) - \Delta\boldsymbol{C}_M(u_1) = [\, 2, 1, 2, 1, 2, 1\,] - [\, 1, 0, 1, 1, 1, 1\,] = [\, 1, 1, 1, 0, 1, 0\,].$$

Therefore, the overall *diagnosis error* $\Xi(u_k, \Delta\boldsymbol{C}(u_k))$ of a decision of misconception set $\Delta\boldsymbol{C}(u_k)$ comes from the total sum of the above two types of errors $\boldsymbol{\alpha}(u_k)$ and $\boldsymbol{\beta}(u_k)$. Formally, this diagnosis error can be symbolized as:

$$\Xi(u_k, \Delta C(u_k)) = |\boldsymbol{\alpha}(u_k)|_{ci \in \boldsymbol{C} \setminus \varsigma(uk)} + |\boldsymbol{\beta}(u_k)|_{ci \in \Delta\mathbf{C}(uk)} = \Sigma_{ci \in \boldsymbol{C} \setminus \Delta\mathbf{C}(uk)} \Delta C_i(u_k) + \Sigma_{ci \in \Delta\mathbf{C}(uk)} (\boldsymbol{CD}(\boldsymbol{q})_i - \Delta C_i(u_k)). \tag{12}$$

Then Problem 1 has a formal formulation for optimization: to determine the misconception set $\Delta\boldsymbol{C}(u_k)$ such that

$$arg\ min_{\Delta\mathbf{C}(uk)}\ \Xi(u_k, \Delta\boldsymbol{C}(u_k)). \tag{13}$$

Any solution satisfying (12) is called *the optimal solution* for Problem 1.

D. Optimal Diagnosis Algorithm

Seemingly, the problem of making up a decision whether a concept is a misconception ($c_i \in \Delta C(u_k)$) or not is just to select a smaller value between $\alpha_i(u_k)$ and $\beta_i(u_k)$ to lower the overall error. However, these concepts are located in a concept hierarchy $\boldsymbol{CH}(\boldsymbol{C},\boldsymbol{R})$, which implies these misconceptions will influence to each other. As shown, $\alpha_i(u_k)$ and $\beta_i(u_k)$ provide indicator of type I and type II errors within a single concept node c_i. However, there are nesting (hierarchical) relationships

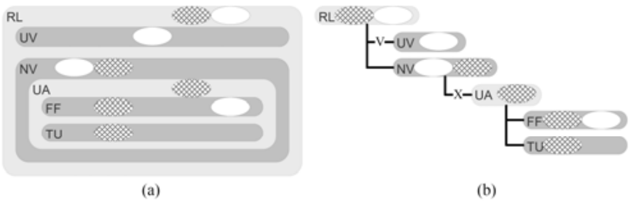

Fig. 3. Concept hierarchy depicted in (a) set inclusion diagram and (b) tree structure

among concepts, i.e. a selection of as c_i a misconception means all its sub-concepts are also misconceptions. Under this circumstance, the counting of type I/II errors can not only consider the concept itself, but also have to encompass all the sub-concepts. The following formulae illuminate such calculation:

1) type I cumulative error

$$\begin{aligned}\boldsymbol{\alpha}^{\mathbf{C}}(u_k) &= \Delta \boldsymbol{C}^{\mathbf{C}}(u_k)\\ &= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C})))\cdot\boldsymbol{\alpha}(u_k)\\ &= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C})))\cdot\Delta\boldsymbol{C}(u_k), \text{ and} \quad (14A)\end{aligned}$$

2) type II cumulative error

$$\begin{aligned}\boldsymbol{\beta}^{\mathbf{C}}(u_k) &= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C})))\cdot\boldsymbol{\beta}(u_k)\\ &= (\boldsymbol{CHM}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})) + \boldsymbol{I}(length(\boldsymbol{C})))\cdot(\boldsymbol{CD}(\boldsymbol{q}) - \Delta\boldsymbol{C}(u_k))\\ &= \boldsymbol{CCD}(\boldsymbol{q})_i - \Delta\boldsymbol{C}^{\mathbf{C}}(u_k). \quad (14B)\end{aligned}$$

For the previous example,

$$\begin{aligned}\boldsymbol{\alpha}_{\text{Motion}}{}^{\mathbf{C}}(u_1) &= \Delta\boldsymbol{C}_{\text{Motion}}{}^{\mathbf{C}}(u_1)\\ &= [\,5, 0, 4, 3, 1, 1\,]\end{aligned}$$

and

$$\begin{aligned}\boldsymbol{\beta}_{\text{Motion}}{}^{\mathbf{C}}(u_1) &= \boldsymbol{CCD}(\mathbf{q}_{\text{Motion}}) - \Delta\boldsymbol{C}_{\text{Mion}}{}^{\mathbf{C}}(u_1)\\ &= [\,9, 1, 6, 4, 2, 1\,] - [\,5, 0, 4, 3, 1, 1\,]\\ &= [\,4, 1, 2, 1, 1, 0\,].\end{aligned}$$

Now, it is possible to design an algorithm for the optimal solution of the learning diagnosis in Problem 1. Principally, such algorithm is based on the type I and type II errors defined in (11A), (11B), (14A) and (14B), as described in the following.

Algorithm 3 (Optimal algorithm for learning diagnosis): Given a concept hierarchy $\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})$, a test sheet $\mathbf{q}$ = [$t(prop_j(c_i,...x))$] and a standard answer sheet $\mathbf{a}^*$ = [a_j*] with embedded concepts $\boldsymbol{ECM}(\mathbf{q})$ = [$\boldsymbol{EC}(t(prop_j(c_i,...x)))$]. For a learner u_k with an answer set $\mathbf{a}(u_k)$, to find his/her correct concept set $\boldsymbol{\eta}(u_k) \subseteq \boldsymbol{C}$ and his/her misconceptions set $\Delta\boldsymbol{C}(u_k) \subseteq \boldsymbol{C}$ with the minimized diagnosis error $\Xi(u_k, \Delta\boldsymbol{C}(u_k))$.

1) Determine $\boldsymbol{CHcode}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ and $\boldsymbol{CHM}(\boldsymbol{C})$ through Algorithm 1.
2) Find $\boldsymbol{CECM}(\mathbf{q})$, $\boldsymbol{CD}(\mathbf{q})$ and $\boldsymbol{CCD}(\mathbf{q})$ from (5), (4) and (6), respectively.
3) For the given answer set $\mathbf{a}(u_k)$, calculate $\boldsymbol{\Delta}\mathbf{a}(u_k)$.
4) Determine type I error $\boldsymbol{\alpha}(u_k) = \Delta\boldsymbol{C}(u_k)$ and cumulative type I error $\boldsymbol{\alpha}^{\mathbf{C}}(u_k) = \Delta\boldsymbol{C}^{\mathbf{C}}(u_k)$ in (8), (9), (11A) and (14A).
5) Subsequently, compute type II error $\boldsymbol{\beta}(u_k) = \boldsymbol{CD}(\mathbf{q}) - \Delta\boldsymbol{C}(u_k)$ and cumulative type II error $\boldsymbol{\beta}^{\mathbf{C}}(u_k) = \boldsymbol{CCD}(\mathbf{q}) - \Delta\boldsymbol{C}^{\mathbf{C}}(u_k)$ in (11B) and (14B).
6) $\boldsymbol{\eta}(u_k) = \Delta\boldsymbol{C}(u_k) = \{\}$ initially.
7) For all concepts c_i's in the column order of $\boldsymbol{CHcode}(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$, i.e. in the pre-order of $\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R})$, perform the following checks.
  7A) Find the path from $root(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))$ to c_i, i.e. $\boldsymbol{C}^{\mathbf{P}}(c_i) = \{c_{i1}: root(\boldsymbol{CH}(\boldsymbol{C}, \boldsymbol{R}))\ r_k\, c_{i1} \text{ and } c_{i1}\ r_k\, c_i\}$.
  7B) If $\alpha_i(u_k) \neq \beta_i(u_k)$, and $\forall c_{i1} \in \boldsymbol{C}^{\mathbf{P}}(c_i)$, $c_{i1} \notin \boldsymbol{\eta}(u_k)$ and $c_{i1} \notin \Delta\boldsymbol{C}(u_k)$, make the following decision:
    7B1) If $\alpha^{C}_i(u_k) \geq \beta^{C}_i(u_k)$, add c_i into $\Delta\boldsymbol{C}(u_k)$.
    7B2) Otherwise ($\alpha^{C}_i(u_k) < \beta^{C}_i(u_k)$), add c_i into $\boldsymbol{\eta}(u_k)$.

With this algorithm, not only all concepts fall in $\boldsymbol{\eta}(u_k)$ or $\Delta\boldsymbol{C}(u_k)$, that is, $\boldsymbol{\eta}(u_k) \cup \Delta C(u_k) \neq \boldsymbol{C}$. And the rest concepts $\boldsymbol{C} \setminus \boldsymbol{\eta}(u_k) \setminus \Delta\boldsymbol{C}(u_k)$ denote those concepts may be correct concepts or misconceptions since $\alpha_i(u_k) = \beta_i(u_k)$, $\forall c_{i1} \in \boldsymbol{C} \setminus \boldsymbol{\eta}(u_k) \setminus \Delta\boldsymbol{C}(u_k)$.

Before the implementation of this algorithm, we have to prove the optimality of the proposed solution. As mentioned, such optimality comes from the minimization of the corresponding diagnosis error $\Xi(u_k, \Delta C(u_k))$. Continuing the previous example, $\Delta C(u_1)$ = { UA } and $\boldsymbol{\eta}(u_1)$ = { UV }, and the minimized diagnosis error $\Xi(u_1, \Delta C(u_1)) = 3$. Such selection and errors can be illustrated by a set-inclusion graph in Fig. 3a and by a hierarchical concept tree in Fig 3b. Note that the choice of correct concept set $\boldsymbol{\eta}(u_1)$ makes no error, the choice of misconception set $\Delta C(u_1)$ makes one type II error, but there are still two possible errors in RL and NV, which can be either type I or type II errors, depending on the concepts are chosen as correct concepts or misconceptions.

V. Practical Applications

After the algorithms for learning diagnosis are developed, we still have to look into some practical considerations before putting these algorithms into pedagogical use. The first issue to bring out is the design format of the test sheet, including questions, answers and the embedded concepts. This test sheet format is expected to be compatible to some International courseware standards, such as SCORM (Sharable Content Object Reference Model). [1] The essential problem for our implementation is to transform the above-mentioned algorithm into actual processes, built on the specified workable platform. Finally, the accomplished software is packaged as an Internet learning assessment system and practically used in several pedagogical markets.

A. *Test Sheet Design with International Standards*

Document structures represented by XML, is characterized by DTD (document type definition). In this circumstance, it is better to set up our test sheet format through XML, i.e. describing questions, answers and the embedded concepts by DTD.

There are many ready-made International DTD standards for courseware exchange, such as DoD (department of defense) SCORM, Dublin core, IBM IMS [12], IEEE LOM (learning object metadata) [18]. As the basic granularity of contents, SCOs (sharable content objects) wrap one or more assets, e.g. text, media, data, assessment, as homepages and deliver to learners through LMS (learning management system) or corresponding APIs (application programming interfaces). The contents in SCORM are defined through CSF (content structure format), which is the foundation of our test sheet.

Besides SCORM, we integrate the international standard IMS from the National Learning Infrastructure Initiative of EDUCAUSE. [12] IMS contains many meta-data information definitions, including question, question types, question options, all of which are very useful for the establishment of answers and concepts in questions. The mappings between these two international standards and the elements of learning diagnosis are listed in Table VI. An example test sheet in homepage is shown in Fig. 4.

TABLE VI
MAPPINGS AMONG TEST SHEET AND STANDARDS

Elements of test sheets		Tag category	Tag	Example
test title	**SCORM**	<general>	<title>	Physics 2.2
concepts			<keywords>	rectilinear motion
test source		<educational>	<learningresourcetype>	XYZ junior school
difficulty			<difficulty>	2
Test time			<datetime>	04/11/2003
institution		<rights>	<description>	
question	**IMS**	<material>	<mattext>	$q_{M1}=prop_{M1}(x)$
Item type		<response_lid>	<rcardinality>	single
answer label			<response_label>	(A)
answer text			<mattext>	12.4
standard answer				$a_{M1}^* =$ "C"

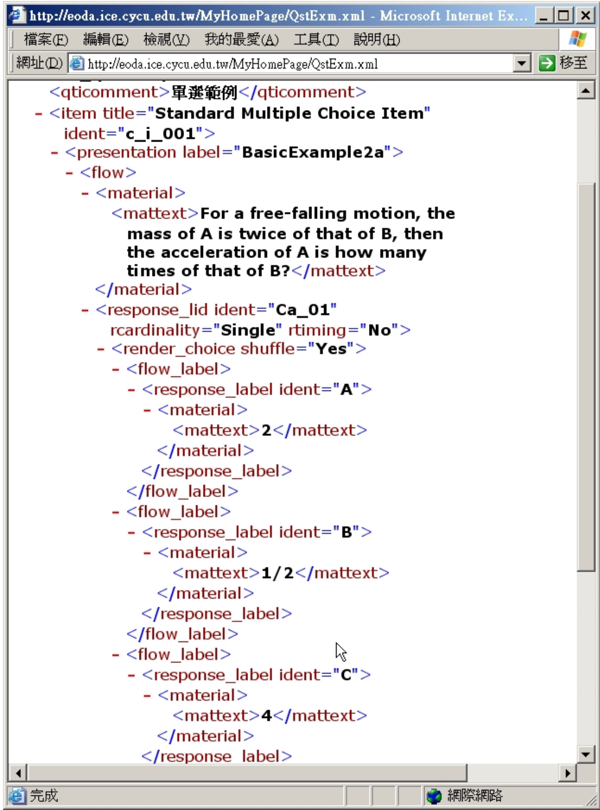

Fig. 4. An example test sheet

B. *A Real System and its Operations*

The resultant system structure is illustrated in Fig. 5, in which learners can take part in an on-line test through browsers and after testing, get their learning diagnosis results in a real-time way. As shown in this system, there are two main databases: one for knowledge base (more precisely, concept hierarchy) and the other for item bank. Each database owns its own editor for editing the hierarchical concepts and test items, as shown in Fig. 6. An internet test environment includes learner identification and flow control, in Fig. 7. Of course, a learning diagnosis includes misconceptions ($\Delta C(u_k)$) as well as other details for the test, as shown in Fig. 8.

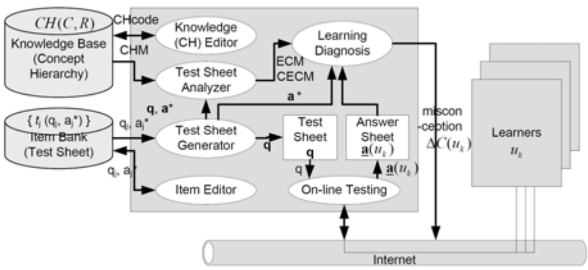

Fig. 5. The practical on-line testing and learning diagnosis system

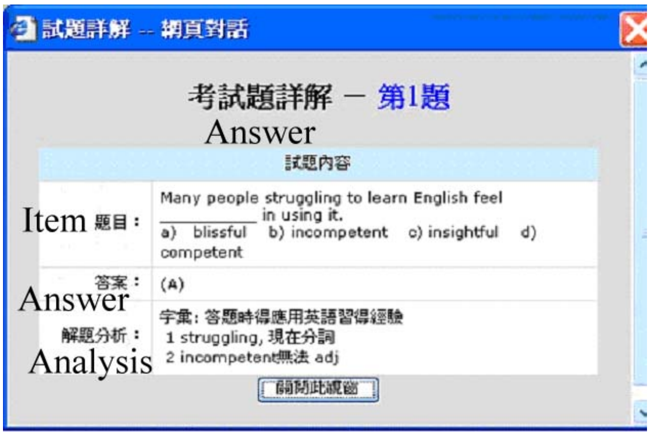

Fig. 6. Item editor for analyzing a test item

There are totally more than 5000 members for this system and each monthly Internet test attracts more than 500 members. The members are all the students for the third grade of junior high school and come from all over Taiwan. For each test, there are 11 courses, from Chinese, English, Physics, History to Earth Science, just as those subjects to be chosen in the entrance examination of high schools in Taiwan.

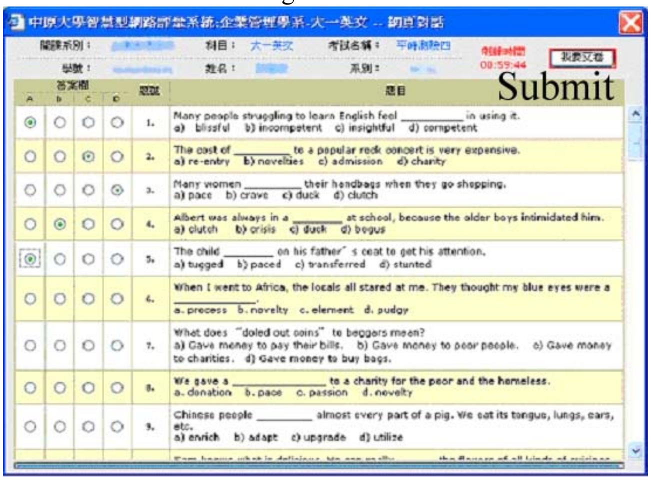

Fig. 7. A snapshot for on-line testing

Fig. 8. A simple learning diagnosis report

VI. Conclusion

Based on the embedded concept hierarchy of a test sheet, this paper explores the possibility of learning diagnosis for Internet testing and establishes a real system to prove its practicability. First of all, such concept hierarchy originates from the part-of and type-of relationships among concepts and its hierarchical codes possess many useful properties. For a test sheet, all the concepts embedded in test items can be collected in several matrices ***ECM***/***CECM***/***NCECM***. Therefore, some kinds of concept errors are calculated according to the answers that learners hand in. There are two algorithms proposed here, these algorithms are realized by a practical Internet system to provide distance assessment with on-line testing and real-time learning diagnosis.

Continuing the above development, we still many works to do. The first thing is for a class under test, to investigate the group misconceptions and to develop such learning diagnosis report. This must be useful for the teacher. On the other hand, we can apply the above diagnosed results to learners and feedback them with personalized learning materials. Different learners with different misconceptions gain different kinds of learning materials. These experiments are both ongoing now, and the results will be reported soon.

References

[1] ADL (Advanced Distributed Learning Project), 2006, [Online]. Available: http://www.adlnet.org/.

[2] B. A. Davey and H. A. Priestley, *Introduction to Lattices and Order, Cambridge*, Cambridge University Press, 1990

[3] B.J.F. Meyer, *Signaling the structure of text*, cited in D.H. Jonassen Ed. Vol.2, Englewood Cliffs, NJ: Educational Technology Publications, 1985

[4] C. D. Holley, D. F. Dansereau, B. A. McDonald, J. C. Garland and K. W. Collins, "Evaluation of a hierarchical mapping technique as an aid to prose processing," *Contemporary Educational Psychology*, 1979, pp.227-237

[5] C. K. Hsu, J. C. Chang, M. Chang, J. C. Jehng and J. S. Heh, "An Approach for Automatic Learning and Inference by Knowledge Map," *International Conf, on Computer Education (ICCE)*, 2002, Auckland, New Zealand

[6] D. F. Dansereau and C. D. Holley, *Development and evaluation of a text mapping strategy*, in A. Flammer & W. Kintsch Eds., Discourse Processing. Amsterdam: North Holland, 1982

[7] D. F. Dansereau, *The development of a learning strategies curriculum*, as cited in H. F. O'Neil, Jr. Ed., Learning strategies. New York: Academic Press, 1978

[8] D. Keegan, *Foundations of Distance Education*, 2nd ed, 1990, New York: Routledge.

[9] D. P. Ausubel, J. D. Novak, H. Hanesian, *Educational psychology: A cognitive view*, 2nd. Ed., New York, Holt, Rinehart and Winston, 1978

[10] D. X. Dong, "*Apply knowledge Map to develop physics Problem-Solving System*," M.S. thesis, Dept. Information and Computer Eng., Chung Yung Christian Univ., Taiwan, 2002

[11] H. Jiawei and F. Yongjian, "Dynamic Generation and Refinement of Concept Hierarchies for Knowledge Discovery in Database", In Proc. *AAAI* Workshop on Knowledge in Databases. 1994

[12] IMS (Instructional Management Systems Project), 2006, [Online]. Available:. http://www.imsproject.org/.

[13] J. D. Novak and D. Gowin, *Learning to learn*. Cambridge: Cambridge University Press, 1984

[14] J. D. Novak and D. R. Ridley, *Assessing student learning in light of how students learn,* Washington, DC, American Association for Higher Education, 1988

[15] J. D. Novak, *Learning theory applied to the biology classroom*, The American Biology Teacher, 42, 1980, pp. 280-285

[16] K. M. Markham, J. J. Mintzes and M. G. Jones, "The concept map as a research and evaluation tool: Further evidence of validity," *Journal of Research in Science Teaching*, 31(1), 1994, pp. 91-101.
[17] L. L. Robert and E.G. Norman, *Measurement and Assessment in Teaching*, 7th ed., Prentice-Hall, Inc. 1995, pp. 115-198.
[18] LTSC (IEEE Learning Technology Standards Committee). (2006). [Online]. Available: http://ieeeltsc.org/
[19] M. Clifford, "The frame game", in *Syke* Ed, Supplement to Practicing educational psychology, New York, Houghton Mifflin, 1981
[20] M. R. Quillian, *Semantic Memory*. Cambridge: Bolt, Beranek & Newman. 1966
[21] P. F. W. Preece, "Mapping cognitive Structure: A comparison of methods," *Journal of Educational Psychology*, 68, 1976, pp. 1-8
[22] R. D. Tennyson and M. J. Cocchiarella, An empirically based instructional design theory for teaching concepts, Review of Educational Research, 56, 1986, pp. 40-71
[23] R. E. Mayer, *Educational psychology: A cognitive approach. Boston, MA: Little*, Brown and Co. 1987
[24] R. K. Hambleton and H. Swaminathan, *Item response theory: Principles and applications*, Boston: Kluwer-Nijhoff, 1985
[25] R. Kuo, M. Chang, D. X. Dong, K.-Y. Yang and J. S. Heh, "Applying Knowledge Map to Intelligent Agents in Problem Solving Systems," *World Conf. on Educational Multimedia, Hypermedia & Telecommunications (ED-Media)*, 2002, Denver, Colorado, USA
[26] R. P. Grimaldi, *Discrete and Combinatorial mathematics: an applied introduction*, 3rd ed., Addison-Wesley Publishing Company, Inc., 1994, pp.51-100.
[27] XML (Extensible Markup Language). (2006). [Online]. Available: http://www.w3.org/XML/.
[28] Y. Y. Lin, "*Applying Concept Hierarchy to Diagnose Misconceptions in Distance Testing*", M.S. thesis, Dept. Information and Computer Eng., Chung Yung Christian Univ., Taiwan, 2002