A hybrid cognitive assessment based on ontology knowledge map and skills

Xiuqin Zhong a,⇑, Hongguang Fu a, Huadong Xia b, Leina Yang a, Mingsheng Shang a

a School of Computer Science and Engineering, University of Electronic Science and Technology of China, Chengdu, China
b Department of Computer Science, Virginia Tech, Blacksburg, USA

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A B S T R A C T
An intelligent tutoring system plays vital role in education and its importance is constantly increasing, meanwhile the key challenge in the teaching learning process is assessing students' learning efficiently. In this paper, a hybrid assessment based-on ACT-R cognitive learning theory, combining ontology knowledge map with skills is proposed. In order to assess how well students master knowledge structure, an ontology knowledge map is constructed to describe declarative knowledge; and in order to assess how well students master knowledge skills, a problem solving process is constructed to describe procedural knowledge based on ACT-R. Finally, a student’s mastery of knowledge is assessed through both the knowledge map and skills in the problem solving process, as well as auxiliary indicators like time usage, prior knowledge level, self-assessment, etc. This method is implemented in a geometric intelligent assessment system and is evaluated in a junior high school. Experiments show that the assessment results are consistent with students' actual learning levels. The hybrid cognitive assessment method can not only obtain the score of students' mastery of knowledge points and the structure through knowledge map, but also assess the learning skills in problem solving process through exercises quantitatively.

1. Introduction

An Intelligent Tutoring System (ITS) plays vital role in education and its importance is constantly increasing [1]. As we know, ITS is a computerized learning environment that incorporates computational models from the cognitive sciences, learning sciences, computational linguistics, artificial intelligence, mathematics, and other domains [2]. ITS can provide directed, customized and individualized instruction or feedback to learners [3]. Furthermore, it offers educational materials suitable for a learner's learning style, knowledge, interests and abilities, adapts the learning environment to the learner's preferences, executes adaptive tests appropriate to the learner's current knowledge level, and it is flexible in time and space [4].

While the key challenge in the teaching learning process of ITS is assessing the students' learning [1]. Assessments are usually used to improve the quality of instruction in the teaching learning process [5]. Therefore, the development of good assessment and feedback techniques is essential to the development of reliable tutoring systems in domain [6].

As is well known, traditional assessment methods are standard paper–pencil tests, which assess how students master knowledge by marks.

With the development of computer-aided instructions, the research on how to assess a student’s mastery of knowledge arises more and more interests, and some new methods have been proposed.

One of them is the knowledge map or knowledge mapping. Knowledge map was proposed by Joseph D. Novak, professor of Cornell University, in 1960s, which can express the definitions, thinking and theories in the form of a graph structure. So it captures the relationships between concepts and can provide users with effective navigation. Especially in ITS, knowledge map is widely used as an effective assessment tool.

For example, based on Bloom's Taxonomy of Educational Objectives, knowledge maps with various difficulty levels are provided to students with different knowledge levels, allowing them to construct these maps for assessment, then adaptive knowledge assessment can be achieved by this method. Wu et al. [7] found the effectiveness of concept map as assessment tool. An assessment system based on Multi-Agent Intelligent knowledge map was proposed in [8]. The psychometric characteristics and practicality of concept mapping as a technique for classroom assessment were...
evaluated in literature [9], but it only took into account (a) the time required to train students to create concept maps; (b) the time required for students to create concept maps; and (c) the time required to score concept maps. [10] developed Human Performance Knowledge Mapping Tool (HPKMT), which enables trainees to express their understanding of a content area by creating graphical, network representations of concepts and links that define the relationships of concepts. Furthermore, literature [11] proposes concept map based on assessment from students learning using ontology mapping, and literature [11] presents different results and studies around the world about the Fuzzy Cognitive Maps.

But there are deficiencies in traditional knowledge maps. On one hand, they are static and knowledge has to be updated manually, which is time consuming and inefficient. On the other hand, concepts, rules and relationships between concepts of different knowledge maps are quite different from each other. Therefore, knowledge map is still not enough to fulfill a cognitive assessment of learning.

Concept map can be used to enhance the interaction of teaching and learning with the goal to foster problem solving skills [12]. Therefore, the ultimate goal for students is to train problem solving skills, so that they can work out problems correctly.

Some researches on how to assess problem solving skills are also proposed. Desmarais and Baker [13] reviewed the learner models and the latest advances in the modeling and assessment of learner skills. Walker et al. [14] developed models in computer-mediated peer tutoring by problem-solving context. Augustin et al. [15] uses Markov Chain procedure to assess skills with Competence-based Knowledge Structures. The results in [16] can be applied to construct efficient algorithms for the adaptive assessment of knowledge, including prerequisite relationships, but it did not yet take into account the possibility that students may make careless errors or lucky guesses. Observation of actual online interactions between tutors and students provides information related to the processes used in problem solving, which is useful for building dialog or interactivity in tutoring systems [17]. A fuzzy assessment method to assess special skills of mechanical manipulation is mentioned in [18] for improving the reliability of assessment. A multidimensional model to assess proof comprehension in undergraduate mathematics is proposed in [19], but it can be assessed in the context of proof only in number theory. Literature [20] uses intelligent assessor to make the learning process (such as a proof of concept) effective and efficient through appropriate individualized feedback. Furthermore, cognitive decision support in digital ecosystems is concerned with cognitive processes for better decisions [21].

According to the above investigations, an assessment combing onto knowledge map and skills based on ACT-R is proposed in this paper. In ACT-R model, knowledge is divided into declarative knowledge and procedural knowledge [22]. Therefore, ontology knowledge map used to describe declarative knowledge is constructed in order to assess how students master knowledge structure, and exercises based on problem solving process used to describe procedural knowledge are provided in order to assess how students master skills. Furthermore, an assessment system based on the assessment result of knowledge map and skills is built to evaluate students’ learning levels. We also conduct a real case study in geometry and run experiments to show the efficiency and intelligence of the assessment method.

In Section 2, the structure of knowledge map and skills of problem solving will be described respectively. In Section 3, a hybrid cognitive assessment combining knowledge map with skills in problem solving process will be proposed. In Section 4, a geometry intelligent assessment system will be implemented based on the hybrid cognitive assessment algorithm, and two experiments will be tested in detail.

2. Knowledge map and skills

In this section we introduce the process of building declarative knowledge and procedural knowledge on ontology, then describe a structure assessment based on ontology knowledge map and a skill assessment based on problem solving respectively.

2.1. Structure of knowledge map

It is necessary to construct an ontology for adaptive knowledge map. An ontology is a formal, explicit specification of a shared conceptualization, representing knowledge as a set of concepts within a domain and the relationships between those concepts [23].

Concepts of a disciplinary ontology constructed in this paper contain declarative knowledge such as definitions, theorems, propositions, skills, the methods it employs, and specific examples it relates to. The disciplinary ontology in our assessment model mainly includes three classes: knowledge topic, skill and knowledge point. Knowledge topic is a learning target in a certain section during students’ learning process. Skill is a special method during problem solving process related to the knowledge topic. Knowledge point is either a definition, a theorem or a proposition related to the knowledge topic. Relationships of the disciplinary ontology constructed in this paper contain not only traditional relationships such as SubclassOf and SubpropertyOf, but also domain relationships such as HasKnowledge, HasSkill, HasExample. One framework of the knowledge ontology is shown in Fig. 1.

In Fig. 1, a knowledge topic is usually related to skills, including $S_1, S_2, \ldots, S_n$. $HasSkill$ represents relationships between knowledge topics and skills. A skill is usually related to knowledge points, such as $P_1, P_2, \ldots, P_n$, and then $HasKnowledge$ represents relationships between skills and knowledge points. In addition, $HasSkill(T,S)$ means the prerequisite of grasping knowledge topic $T$ is grasping skill $S$. $HasKnowledge(S,P)$ means the prerequisite of grasping skill $S$ is grasping knowledge point $P$. $HasKnowledge(S,P_1) \land HasKnowledge(S,P_2) \land HasKnowledge(S,P_3)$ means the prerequisite of grasping skill $S$ is grasping knowledge points $P_1, P_2$ and $P_3$.

For example, suppose knowledge topic $t_1$ represents topic of triangles congruent, skill $S_1, S_2, S_3$ represents skills of proving Triangle Congruence using SSS Congruence Theorem, SAS Congruence Theorem, AAS Congruence Theorem respectively, and knowledge point $P_1, P_2, P_3$ represent knowledge points of SSS Congruence Theorem, SAS Congruence Theorem, and AAS Congruence Theorem respectively. If we want to learn knowledge topic $t_1$, we need to know skill $S_1, S_2$ and $S_3$, so we can get $HasSkill(t_1, S_1) \land HasSkill(t_1, S_2) \land HasSkill(t_1, S_3)$.
we need to know knowledge point \( p_1 \), \( p_2 \) and \( p_3 \) respectively, so we can get \( \text{HasKnowledge}(S_1, p_1) \), \( \text{HasKnowledge}(S_2, p_2) \), and \( \text{HasKnowledge}(S_3, p_3) \).

Once an ontology is built, a corresponding knowledge map can then be constructed dynamically based on the ontology. Furthermore, the knowledge map can display concepts and relationships which are expressed by ontology triples (subject, predicate, object). In Fig. 2, we list a fraction of knowledge map which shows structure of knowledge. Therein, rectangle node represents concept, and direction arrow represents relationship of concepts.

### 2.2. Skills of problem solving

In light of cognitive psychology, “concepts understanding” and “skills training” refers to two different psychological activities. As for procedural knowledge, skills cannot be acquired without repetitious practice. Repetitious practice is an effective way to acquire procedural knowledge, which helps students use concepts to analyze and solve problems. Anderson proposed the ACT-R theory that cognitive skills are actually some rules used in special cases in the process of solving problems. Skills acquisition begins in some examples in the process of solving earlier problems, and the examples will be converted into general rules, which will be used to solve problems later.

In this paper, procedural knowledge mainly indicates the process from derivation conditions to current result according to some reason in solution path. And solution paths of exercises are actually applications of basic knowledge points.

For explanation, an example of exercise is shown in Fig. 3, and one path of problem solving process of the exercise is instantiated in Fig. 4, which refers to the cognitive learning of students. Among which the direction arrow means a conclusion can be obtained from one or more known conditions, different steps in solution paths correspond to different skills, and one skill corresponds to some knowledge points at the same time. In this way, skills can be extracted by learning exercises with problem solving process constantly.

In the following, a hybrid cognitive assessment combining knowledge map and skills is described in detail, including algorithm of assessment on ontology knowledge map and flow chart of assessment on skills of problem solving.

### 3. A hybrid cognitive assessment combining knowledge map with skills

#### 3.1. Assessment on ontology knowledge map

The algorithm of knowledge map assessment is described in Table 1.

Firstly, after students study a certain knowledge topic, a knowledge map composed of the knowledge points relating to this topic
Table 1
Knowledge map assessment algorithm.

<table>
<thead>
<tr>
<th>Algorithm: Knowledge map assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Input:</strong> An ontology knowledge map</td>
</tr>
<tr>
<td><strong>Output:</strong> Assessment results</td>
</tr>
<tr>
<td>Step 1. Display a knowledge map of some knowledge topic</td>
</tr>
<tr>
<td>Step 2. Fill the knowledge map</td>
</tr>
<tr>
<td>Step 3. Check if the knowledge map is accomplished. If so, record the filling time and compute the correctness for assessment. Otherwise, return to Step 2</td>
</tr>
<tr>
<td>Step 4. Feedback the assessment result</td>
</tr>
</tbody>
</table>

The students are asked to fill the knowledge map. Then the map will be submitted to the assessment system automatically once it is completed by student. In the meanwhile, the correctness and the time for filling the knowledge map by every student will be recorded, then the knowledge map will be assessed. First of all, knowledge map is split into a series of triples. Then, triples in knowledge map filled by students are compared with those stored in system. A triple equals to another if they have the same subject, predicate and object.

Finally, the assessment results are fed back to students, so that they know whether a knowledge point is comprehended or not. Such automatic and instructive assessing mechanism will not only give an accurate evaluation to the study effect of students, but also improve their cognitive structure and study efficiency.

3.2. Assessment on skills of problem solving

Students' mastery of skills is assessed by problem solving process, and the flow chart of skill assessment is shown in Fig. 5.

After students study certain knowledge topic, an exercise custom-built to the topic is selected to assess students' mastery of corresponding skills.

Then students begin to do the exercise step by step. Score corresponding to the skill will be increased when one step in solution path is completed, and it shows that students have mastered the skill. Otherwise, score corresponding to the skill will be decreased when one step in solution path is not completed.

In the end, students' mastery of the knowledge points corresponding to the skills will be modified. To some degree, the score of skills can evaluate students' mastery of the corresponding knowledge points.

According to the above descriptions, ontology knowledge map used to describe declarative knowledge is constructed to assess how well students master knowledge structure, and exercises based on problem solving process used to describe procedural knowledge are provided to assess how well students master skills. The flow chart of the hybrid cognitive assessment process is shown in Fig. 6.

At the beginning, students start to learn basic concepts and skills. Then students' mastery of structure is assessed through knowledge map, and students' mastery of skills is assessed through problem solving. During the process, students can improve themselves by learning and assessing iteratively.

After that, an assessment method is closely proposed combining knowledge map and skills with other indicators by the algorithm of synthetic fuzzy assessment, and students are assessed ultimately.

3.3. A hybrid cognitive assessment

In almost all assessment systems, accuracy and time-usage are most important indicators. In this paper, knowledge map and skills of problem solving process are combined together, so indicators including accuracy of knowledge map, accuracy of skills in exercise, time-usage of knowledge map, time-usage of skills in exercises are used in this assessment.

Furthermore, knowledge based systems could make intelligent decisions based on prior knowledge [24], and Thai-Nghe et al. [25] uses a tensor factorization forecasting models the sequential learning effect to predict student performance. What is more, there is a saying, practice makes perfect, if some student learn prior knowledge well, he can easily learn subsequent knowledge, especially in subjective learning. Then grasping level of prior knowledge is regarded as one indicator in the assessment.

Generally speaking, every student should be the one who understands himself mostly, especially in learning. Biswas et al. [26] developes a self-regulated learning model that can identify a range of behaviors through self-assessment. Although self-assessment is considered as a subjective parameter to assess a student's level, it can objectively represent one's actual level in practise.

So the six indicators such as accuracy of knowledge map, accuracy of skills in exercise, time-usage of knowledge map, time-usage of skills in exercises, grasping level of prior knowledge and self-assessment are combined together, and they are explained in the following with more details.

(a) The accuracy of the knowledge map filled by students. This index is to evaluate students' memory and understanding in cognition of knowledge points correctly, denoted as ind-1.

(b) The time students spend filling in the knowledge map, which can evaluate students' proficiency in cognition of knowledge points in some way. In addition, every knowledge map will be associated with a baseline time length, which is compared to the time students spend filling in the knowledge map. The ratio of time against the baseline time is denoted as ind-2.
The accuracy of exercises in the skill assessment, which can evaluate students' mastery of skills accurately and assess comprehensive applications in cognition of corresponding knowledge points indirectly. It’s denoted as Ind-3.

The time students spent finishing exercises in the skill assessment, which can evaluate students' proficiency of skills in cognition. The ratio of the time against the baseline time is denoted as Ind-4.

The grasping level of prior knowledge. For example, the prior knowledge of \( K_1 \) is \( K_2 \) and \( K_3 \), that is to say a student cannot master \( K_1 \) until he has mastered \( K_2 \) and \( K_3 \). So grasping level in cognition of prior knowledge can evaluate students knowledge level. It is denoted as Ind-5.

Self-assessment. A student can evaluate intellectual level according to his study subjectively. It is denoted as Ind-6.

In order to assess comprehensively, in addition to knowledge map (Ind-1) and skills (Ind-3), the above 4 auxiliary indicators (Ind-2, Ind-4, Ind-5, Ind-6) are introduced in the assessment method. All assessment indicators are analyzed by fuzzily integrated assessment method. Because of all assessment indicators located in the same hierarchy, a fuzzy synthetic assessment model is used in this paper.

Firstly, two sets are provided.

\[
U^r = \{u_i | i = 1, \ldots, 6\} \quad (1)
\]

\[
V = \{v_i | i = 1, 2, 3\} \quad (2)
\]

In Eq. (1), \( U \) represents a set of all assessment indicators. In Eq. (2), \( V \) represents a set of different levels. According to the evaluation, \( V \) is divided into three degrees; Good(G), Medium(M) and Poor(P). That is to say, \( V \) can represent the degree of Good, Medium or Poor respectively. As for the assessment indicator whose index is \( i \) \((i = 1, 2, \ldots , 6)\), the single factorial assessment result is \( R_i = (r_{i1}, r_{i2}, r_{i3}) \), so the decision matrix of these six assessment indicators is expressed as formula (3)

\[
R = U \times V = \begin{bmatrix}
    r_{11} & r_{12} & r_{13} \\
    r_{21} & r_{22} & r_{23} \\
    r_{31} & r_{32} & r_{33} \\
    r_{41} & r_{42} & r_{43} \\
    r_{51} & r_{52} & r_{53} \\
    r_{61} & r_{62} & r_{63}
\end{bmatrix} \quad (3)
\]

Eq. (3) is a fuzzy relation from \( U \) to \( V \).

Secondly, the weight of each assessment indicator is determined using Analytic Hierarchy Process (AHP) [27] \( A = \{a_1, a_2, a_3, a_4, a_5, a_6\} \) (Obviously, \( A \) is a fuzzy subset of \( U \), and \( 0 \leq a_i \leq 1, \sum a_i = 1 \)). By fuzzy transformation and synthetic calculation, a fuzzy subset of \( V \) can be calculated by the hybrid cognitive assessment method.

\[
B = A \times R = \{b_1, b_2, b_3\} \quad (4)
\]

In Eq. (4), \( b_1 \) represents the proportion in degree G, \( b_2 \) represents the proportion in degree M, \( b_3 \) represents the proportion in degree P. And the largest proportion means the degree of students' mastery of knowledge points.

4. Assessment system and its applications

The hybrid cognitive assessment algorithm in Section 3 is used and an ontology of junior high school geometry is constructed using protégé3.4.4, then a geometry intelligent assessment system is implemented using java.

Experimental environment parameters are as follows: CPU: AMD Athlon (tm) X2 240 Processor 2.80 GHz; Memory: 2.00 GB; Operating system: windows XP; Environment: jdk 1.6.0.

In the following, we will give out two experiments executed in our system based on the hybrid cognitive assessment method.

4.1. Experiment 1

In this experiment, an evaluation of one student's mastery of knowledge “triangle” is tested as an example, and the system provides the student with 10 sets of data for evaluation.

An example of knowledge map (as is shown in Fig. 2) with “triangle” produced by our system is shown in Fig. 7. Wherein, rectangle nodes represent concepts, and direction arrows represent relationships of concepts. Therein, (i) represents three sides are equal; (ii) represents there is a right angle; (iii) represents both three sides and three angles of two triangles are equal; (iv) represents there is an obtuse angle; (v) represents theorem; (vi) represents both three sides and three angles of two triangles are equal; (vii) represents three angles are acute. During the assessment, some blanks will appear randomly or the order of learning levels.

Firstly, the system provides one student with 10 knowledge maps which have some blanks as the topic of triangle. He fills out correctly 7 knowledge maps, which accounts for 7/10, and 3 knowledge maps not completely correct, and zero knowledge map completely wrong; Simultaneous the system records the filling time for each knowledge map, and the result is time-usage of 5 knowledge maps less than the standard time, the proportion is 5/10, time-usage of 4 knowledge maps approximately equal to the standard time, and time-usage of 1 knowledge map more than the standard time.

Secondly, the system provides the student with 10 exercises which select triangle as main knowledge point, and records correct rate and time of doing exercises. The correct number is 8 exercises which accounts for 8/10, and the error number is 2 exercises; time-usage of 4 exercises less than the standard time, time-usage of 4 exercises approximately equal to the standard time, and time-usage of 2 exercises more than the standard time.

Next, the system queries the student’s learning records, and obtains his mastering level of prior knowledge of triangle, such
as angle and segment. The student’s mastering level for angle and segment can be calculated by the same hybrid cognitive assessment algorithm.

Finally, the student makes a self-evaluation for the mastering level of the triangle knowledge point. If the student does not conduct the step, the default is medium.

By the time, we can get the value decision matrix in formula (5)

\[
R = \begin{bmatrix}
R_1 & 0.7 & 0.3 & 0 \\
R_2 & 0.5 & 0.4 & 0.1 \\
R_3 & 0.8 & 0 & 0.2 \\
R_4 & 0.4 & 0.4 & 0.2 \\
R_5 & 0.7 & 0.2 & 0.1 \\
R_6 & 0 & 1 & 0 \\
\end{bmatrix}
\] (5)

The weight of each assessment indicator is determined using Analytic Hierarchy Process, we then get

\[
A = \begin{bmatrix}
0.25 & 0.05 & 0.3 & 0.1 & 0.2 & 0.1
\end{bmatrix}
\] (6)

The cognitive assessment result of the student is calculated as:

\[
B = A \times R = \begin{bmatrix}
0.62 & 0.275 & 0.105
\end{bmatrix}
\] (7)

Based on empirical values, we set the value of Good is 0.6, Medium is 0.3, and Poor is 0.1. Based on the result, the student’s mastery of knowledge triangle is evaluated as relatively good.

4.2. Experiment 2

Sixty students from one class in Shilin junior high school in Chengdu, China are selected to test the assessment system by bulk. The class is selected because it contains students with various levels, representing a typical average class. Some classes in the school admit only high score students. What is more, the students in this class have learned elementary geometry by the time. Subsequently, these students are divided into three groups according to their general degrees of learning: Good, Medium or Poor. In the following, the hybrid cognitive assessment process will be explained, which is based on knowledge topic “congruent triangles”.

First, knowledge map as the center of congruent triangles is provided to students, and students’ mastery of knowledge structure (Ind-1) can be assessed. For example, a knowledge map of congruent triangles is instantiated in Fig. 7. At the same time, the degree of time-usage in filling the map (Ind-2) should be recorded.

Second, exercises related to congruent triangles are provided to students, and students’ mastery of relevant skills (Ind-3) will be assessed. Furthermore, solving process of an exercise in Fig. 4 generated by our system is shown in Fig. 8. During skill assessment, the student can finish the process by inputting solving skill or the reason step by step. For example, the problem solving process of congruent triangles is instantiated in Fig. 8. So the corresponding reason, skill and knowledge point (KP) of each statement in problem solving process is shown in Table 2. At the same time, the degree of time-usage in filling the skills (Ind-4) should be recorded.

Third, the system will query learning record and get the students’ level of prior knowledge. The students’ levels of the prior knowledge (Ind-5) are also calculated by our algorithm. Another thing is, the students are suggested to do self-assessment (Ind-6) based on their own knowledge level.

After the above procedure finishes, students’ score of the knowledge map and skills of congruent triangles can then be calculated.

During the process, every two students are selected from each group at random. \(S_1\) and \(S_2\) are selected from the group that students usually get high score (Good) in class. \(S_3\) and \(S_4\) are selected from the group that students usually get average score (Medium) in class. \(S_5\) and \(S_6\) are selected from the group that students usually get low scores (Poor) in class. Note that every two students \(S_1\) and \(S_2\) for each Congruence Theorem (SSS, SAS, ASA, AAS) are different from each other, the same for \(S_3, S_4, S_5\) and \(S_6\). For consistence, we use \(S_1\) and \(S_2\) represent the same degree in each Congruence Theorem.

The whole experimental data is shown in Table 3-a, 3-b, 3-c and 3-d respectively. The experimental result of SSS congruence theorem (SSS) is shown in Table 3-a, the experimental result of SAS...
Given:
(1) $BR = BX$

(2) $IR = IX$

(3) $\triangle BRX$ is isosceles triangle by the definition of isosceles triangle from (1)

(4) $\triangle IRX$ is isosceles triangle by the definition of isosceles triangle from (2)

(5) $\angle BRX = \angle BXR$ by the property of isosceles triangle from (3)

(6) $\angle IRX = \angle IXR$ by the property of isosceles triangle from (4)

(7) $\angle BRX = \angle BXH$ by Equal amount of equivalent is equal from (5),(6)

(8) $B = B$ (Obviously)

(9) $\triangle RBZ \equiv \triangle XBH$ by ASA Congruence Theorem from (1),(7),(8)

Fig. 8. Problem solving process generated by system.

Table 2
Corresponding reason and skill of each statement in Fig. 8.

<table>
<thead>
<tr>
<th>Statement (S)</th>
<th>Reason (R)</th>
<th>Skill Enter Correct Reason and Statement (ECRS)</th>
<th>Knowledge Point (KP)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\triangle BRX$ is isosceles triangle ($S_2$)</td>
<td>The definition of $KP_2$ ($R_2$)</td>
<td>ECRS for $S_2$ and $R_2$</td>
<td>isosceles triangle ($KP_4$)</td>
</tr>
<tr>
<td>$\triangle BRX = \triangle BXR$ ($S_5$)</td>
<td>The property of $KP_2$ ($R_3$)</td>
<td>ECRS for $S_2$ and $R_3$</td>
<td>$KP_2$, angle equal ($KP_5$)</td>
</tr>
<tr>
<td>$IR = IX$ ($S_4$)</td>
<td>Given ($R_1$)</td>
<td>ECRS for $S_2$ and $R_3$</td>
<td>segment equal ($KP_1$)</td>
</tr>
<tr>
<td>$\triangle IRX$ is isosceles triangle ($S_6$)</td>
<td>The definition of $KP_2$ ($R_4$)</td>
<td>ECRS for $S_2$ and $R_4$</td>
<td>$KP_2$, $KP_3$</td>
</tr>
<tr>
<td>$\angle BRX = \angle BXH$ ($S_7$)</td>
<td>Equal amount of equivalent is equal ($R_5$)</td>
<td>ECRS for $S_2$ and $R_4$</td>
<td>equal axiom ($KP_4$)</td>
</tr>
<tr>
<td>$BR = BX$ ($S_8$)</td>
<td>Given ($R_1$)</td>
<td>ECRS for $S_2$ and $R_4$</td>
<td>$KP_1$, $KP_1$</td>
</tr>
<tr>
<td>$\triangle RBZ \equiv \triangle XBH$ ($S_9$)</td>
<td>ASA Congruence Theorem ($R_5$)</td>
<td>ECRS for $S_2$ and $R_5$</td>
<td>ASA Congruence Theorem ($KP_5$)</td>
</tr>
</tbody>
</table>

Table 3-a
The experimental result of SSS.

<table>
<thead>
<tr>
<th>KP</th>
<th>Ind</th>
<th>Good (G)</th>
<th>Medium (M)</th>
<th>Poor (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
<td>$S_2$</td>
<td>$S_3$</td>
<td>$S_4$</td>
</tr>
<tr>
<td>SSS</td>
<td>Ind-1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Ind-2</td>
<td>1.0</td>
<td>0.8</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td>Ind-3</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-4</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-5</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-6</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Score</td>
<td>0.895</td>
<td>0.99</td>
<td>0.796</td>
</tr>
</tbody>
</table>

Table 3-b
The experimental result of SAS.

<table>
<thead>
<tr>
<th>KP</th>
<th>Ind</th>
<th>Good (G)</th>
<th>Medium (M)</th>
<th>Poor (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
<td>$S_2$</td>
<td>$S_3$</td>
<td>$S_4$</td>
</tr>
<tr>
<td>SAS</td>
<td>Ind-1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Ind-2</td>
<td>1.0</td>
<td>0.8</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td>Ind-3</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-4</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-5</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-6</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Score</td>
<td>0.995</td>
<td>0.970</td>
<td>0.784</td>
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</table>

Table 3-c
The experimental result of ASA.

<table>
<thead>
<tr>
<th>KP</th>
<th>Ind</th>
<th>Good (G)</th>
<th>Medium (M)</th>
<th>Poor (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
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<td>$S_3$</td>
<td>$S_4$</td>
</tr>
<tr>
<td>ASA</td>
<td>Ind-1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Ind-2</td>
<td>1.0</td>
<td>0.8</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td>Ind-3</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-4</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-5</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-6</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Score</td>
<td>0.983</td>
<td>0.862</td>
<td>0.804</td>
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</table>

Table 3-d
The experimental result of AAS.

<table>
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<th>KP</th>
<th>Ind</th>
<th>Good (G)</th>
<th>Medium (M)</th>
<th>Poor (P)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
<td>$S_2$</td>
<td>$S_3$</td>
<td>$S_4$</td>
</tr>
<tr>
<td>AAS</td>
<td>Ind-1</td>
<td>1.0</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td></td>
<td>Ind-2</td>
<td>1.0</td>
<td>0.8</td>
<td>0.825</td>
</tr>
<tr>
<td></td>
<td>Ind-3</td>
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<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-4</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-5</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Ind-6</td>
<td>0.953</td>
<td>0.9</td>
<td>0.856</td>
</tr>
<tr>
<td></td>
<td>Score</td>
<td>0.995</td>
<td>0.859</td>
<td>0.752</td>
</tr>
</tbody>
</table>
Congruence theorem (SAS) is shown in Table 3-b, the experimental result of ASA congruence theorem (ASA) is shown in Table 3-c, and the experimental result of AAS congruence theorem (AAS) is shown in Table 3-d.

For example, Table 3-a shows the experimental result of SSS Congruence Theorem. As for Ind-1, students S1, S2, S3 and S4 can fill the corresponding knowledge map correctly, while student S5 and S6 can only fill 80%. As for Ind-2, student S1, S2 and S3 can fill the knowledge map quickly (with degree Good), while student S4, S5, S6 perform normal (with degree Medium). As for Ind-3, student S1 and S2 can fill the skills correctly, while student S3 80%, student S4 82.5%, student S5 65.3% and student S6 42.7%. As for Ind-4, student S2 can fill the exercise quickly (with degree Good), while student S1, S3, S4 and S5 can only be normal (with degree Medium), and student S6 slow (with degree Poor). As for Ind-5, student S1 can grasp the prior knowledge 95.3% correctly, while student S2 90%, student S3 85.6%, student S4 80.3%, student S5 75% and student S6 65.3%. As for Ind-6, student S1, S2, S3 do Self-assessment with degree Good, while student S4, S5, S6 normal with degree Medium. According to empirical value, we set the value of Good is 0.6, Medium is 0.3, and Poor is 0.1. By calculating, the total score of student S1 is 0.895, while student S2 is 0.99, student S3 is 0.796, student S4 is 0.671, student S5 is 0.545 and student S6 is 0.433 respectively. Similarly, we can explain Tables 3-b, 3-c and 3-d.

From Tables 3-a, 3-b, 3-c and 3-d, students' score of corresponding knowledge is assessed respectively through knowledge map, skills and other auxiliary indicators. Experiments demonstrate how well each student masters the knowledge topic of triangles congruent and the corresponding knowledge map and skills.

According to the comparison chart for the score of Tables 3-a, 3-b, 3-c and 3-d of each student, which is shown in Fig. 9, we conclude that scores of students from the good group are significantly higher than scores of students from the medium group, and scores of students from the medium group are significantly higher than scores of students from the poor group. Generally speaking, the experimental results are consistent with students’ actual learning level in practise. Consequently, the hybrid cognitive assessment is reasonable and credible.

5. Conclusion

In traditional ITSs, knowledge points or mass of exercises are usually used to assess students’ learning effects. But knowledge points alone isolate students to understand the relationship of knowledge, and mass of exercises often make students physically and mentally exhausted.

In this paper, a potential knowledge structure based on ontology is constructed, by this way, students will have an integral and macro knowledge structure in their brains, so it's clear for them to learn one knowledge point and it's convenient for them to understand the static relationships of knowledge points, which can solve the problem of seeing the trees but not the forest in learning. In addition, a cognitive knowledge model based on problem solving process is considered, by this way, students will learn a dynamic retrieval process during problem solving process, so it is efficient for them to establish the cause and effect relationship of knowledge points, which can solve the problem of knowing the hows but not the why's in learning process.

What is more, a hybrid cognitive assessment combing knowledge map and skills is proposed. The experimental results show that, the assessment scores our system calculated for the students are consistent with their learning levels in practice, and the hybrid cognitive assessment method can not only obtain the score of students' mastery of knowledge structure through knowledge map, but also assess the learning skills in problem solving process through exercises. That is to say, it is efficient and effective assessment method in ITS. Furthermore, the errors or deficiencies in knowledge maps or a problem solving process can be detected by our system. Students are therefore presented only those problems they are unfamiliar with. They can then be released from heavy exercises due to inefficient repetition.

Based on the assessment method, some recommendation algorithms can be designed for the errors or deficiencies in knowledge maps or problem solving process. Furthermore, if an ontology knowledge map in some domain is constructed, and simultaneously the corresponding skills of exercises with process are provided, then the hybrid cognitive assessment method can be adaptively applied to not only teaching in other subjects such as discrete mathematics, physics and chemistry, but also driving skill training, worker training, psychotherapist training, etc.

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References