Assessing metacognitive knowledge in web-based CALL: a neural network approach

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Abstract

The assessment of learners’ metacognitive knowledge level is crucial when developing computer-assisted language learning systems. Currently, many systems assess learners’ metacognitive knowledge level with pre-instructional questionnaires or metacognitive interviews. However, learners with limited language proficiency may be at a disadvantage in responding to verbal-report interview or questionnaire probes. The goal of this study is to present a neural network model that assesses automatically the learner’s metacognitive knowledge level by observing his/her online browsing behavior. The model is implemented through a multi-layer feed forward neural network. An experiment was conducted to examine the suitability of this model in different Web page structures. One hundred and forty-six college students were categorized into three groups according to three Web page structures: networked, hierarchical, and linear. The experiment results verified the suitability of the proposed model, and the MSEs of assessment of the three groups showed no significant differences with respect to the Web page structures.

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Keywords: Web-based CALL; Metacognitive knowledge; Web page structure; Browsing behavior; Neural network

1. Introduction

As Internet applications become more and more advanced, using Web-based technology to enhance language teaching has become a popular practice among many foreign language/second language (FL/SL) educators (Kern & Warschauer, 2000; Liu, 2001). Since Web-based instruction...
is provided over networked computers utilizing hypermedia and multimedia technology to access various online resources (Brown, 1998; Governor, 1999; Jonassen, 1989), this system indeed offers FL/SL learners a high level of learner control and an abundance of authentic materials that correspond to their learning needs. Moreover, the use of hypermedia learning systems has been claimed to promote a higher level of comprehension development because it requires the association and linking of different ideas and information rather than the recall of facts and data (Paolucci, 1998). As Lanham (1993) suggests, one of the most compelling areas of exploration for computer use is in the field of language learning.

However, Web-based instruction is not without problems. Brown (1998) pointed out that many hypermedia-based courseware designers construct the knowledge nodes arbitrarily. Since learners have total freedom in browsing the Web course, they fail to grasp the more important information effectively. It is also suggested that some learners could experience disorientation and cognitive overload due to the huge quantity of information presented and its lack of organization (Brown, 1998; Governor, 1999; Marchionini, 1988). The above discussion implies that, in general, the structure of the document and the learning strategies used are two important issues involved in Web-based instruction, and courseware designers need to pay close attention to how World Wide Web (WWW) courseware is constructed in the FL/SL curriculum as well as how learners navigate through it.

The influence of metacognitive knowledge on language learning is obvious. Wenden (1998, p. 528) described metacognitive knowledge as “a prerequisite for the self-regulation of language learning: it informs planning decisions taken at the outset of learning and the monitoring processes that regulate the completion of a learning task... and decisions to remediate...”. The literature reviewed generally notes that metacognitive knowledge enhances learning outcomes. It facilitates recall, the comprehension of written texts, the completion of new types of learning tasks, the rate of progress in learning, and the quality and speed of learners’ cognitive engagement (Brown, 1987; Flavell, 1979; Oxford, 1990; Victori, 1995; Wenden, 1998).

Given the importance of learners’ metacognitive knowledge, researchers (e.g., Cotterall, 1999; Jacobs & Paris, 1987; Joe & You, 2001; Oxford, 1990; Victori, 1995; Wenden, 1998) suggested that FL/SL teachers should try to gain an understanding of their learners’ beliefs and knowledge of language learning. Currently, many systems assess students’ metacognitive knowledge level with questionnaires or metacognitive interviews. However, Garner (1988, p. 61) raised specific concerns about collecting verbal-report data from young children and poor readers that “… because of limited language skills, confusion about general processes being queried, or inability to speculate about hypothetical events,” they may be at a disadvantage in responding to interview or questionnaire probes. In fact, methodological problems are not restricted to young children or poor readers. Concerns also exist for FL/SL learners who have diverse proficiency levels for the target language.

To reduce the verbalization demands for respondents, researchers proposed several methodological alternatives to assess learners’ metacognition, for example, cross-age tutoring (Garner, Macready, & Wagoner, 1984), optimal-nonoptimal product method (Bracewell, 1983; Garner, 1988), and stimulated-recall technique (Peterson & Swing, 1983). For users of hypermedia systems, Muller (1999) proclaimed that student’s online browsing behavior offers the potential to extract some psychological information about the student, which may in turn be used to tailor the hypermedia towards the student. He further suggested that neural networks are particularly good
at dealing with very noisy data (Mullier, 2000). The purpose of this paper is to present a neural network system that can assess learners’ metacognitive knowledge level on-line, without having students respond to any interview or questionnaire questions prior to learning. The following section discusses the background of this study.

2. Background of the study

The use of hypermedia as knowledge exploration tools has been attracting much research (Becker, 1993; Jonassen, 1996; Jonassen & Wang, 1993; Paolucci, 1998; Snider, 1992). Jonassen and Wang (1993) and Jonassen (1996) showed that the features of Web-based nodes and links for information representation are like the semantic network of human memory. Since human cognition and memory are Web-based structures comprised of several nodes and links, hypermedia is a good tool to expand human cognitive development and knowledge construction. The nodes and links of hypermedia enable learners to understand the complicated structure of knowledge and the relationship between existing and new structures of knowledge. Researchers generally agreed that using hypermedia-based learning systems stimulates learners’ higher-order thinking ability and creativity, and therefore enhance comprehension, knowledge retention, and transfer learning.

Recently, there are more and more computer-assisted language learning (CALL) systems integrating Web-based interface which features hypermedia and multimedia presentation of information (Kern & Warschauer, 2000). As Federico (2000) mentioned, Web-based CALL allows retrieval and display of multimedia elements, such as videos and audios, which have many pedagogical advantages for language learning. By clicking on certain links, users can jump between sections of the learning materials and learn the materials with their own sequences. Using the WWW, students can search through millions of files around the world within minutes to locate and access authentic materials. They can also use the Web to publish their texts or multimedia materials to share with partner classes or with the general public.

However, as many teachers have enthusiastically embraced the possibilities brought by Web-based CALL, Kern and Warschauer (2000) warned that the technology itself does not bring about improvements in learning. We must look at its use in particular contexts. For instance, Governor (1999) observed that although many learners find success in Web-based environments, others struggle with the challenges of hypermedia. Students with similar educational and professional backgrounds may report a wide range of frustration levels and time requirements to complete Web-based instructional materials. Therefore, how the courseware is structured becomes an important issue. Besides, users’ learning strategies, especially metacognitive strategies, play an important role in constructing complete knowledge in Web-based environments.

According to Paolucci (1998), in order to effectively apply hypermedia to enhance learning, two classes of issues need to be considered. These issues are “authoring-related” and “learning-related”.

2.1. A learning issue: metacognitive knowledge

The learning issue of most concern to Paolucci’s (1998) research study is that of learning strategies in hypermedia. It has been shown that certain learning strategies are more conducive to
the effective use of educational hypermedia than others (Jonassen & Wang, 1993; Larsen, 1992; Lee, 1992). Presently, there is quite extensive literature on the use of learning strategies in FL/SL learning. Many studies showed that students differ in the manner in which they approach language learning (Ellis, 1992; O’Malley & Chamot, 1990; Rubin, 1987). Researchers also claimed that students who use appropriate learning strategies can achieve better results in their learning of a foreign/second language (Holmes & Ramos, 1991; O’Malley & Chamot, 1990; Oxford, 1990). Basically, all agreed that those learners who use a greater variety of strategies tend to be the most successful, and that learning strategies can be trained (Brunig, 1983).

When it comes to the use of educational hypermedia, what type of learning strategy is most likely to be effective in Web-based CALL? Since learner disorientation and cognitive overload are two challenges faced by learners in a hypermedia environment (Brown, 1998; Governor, 1999; Marchionini, 1988), Ganz and Ganz (1990) noted that metacognitive strategies have the potential to empower students to take charge of their own learning, increase perceived efficacy, and decrease the potential for learning helplessness; all of which are desirable learning goals in hypermedia. Oxford (1990) also contended that metacognitive strategies are essential for successful language learning, because language learners are often overwhelmed by too much unfamiliar vocabulary, confusing rules, different writing systems, and social customs. With all this novelty, many learners lose their focus.

Metacognition has been defined as a two-part phenomenon: (1) knowledge about cognition and (2) regulation of cognition (Flavell, 1979). According to researchers (Brown, 1987; Wenden, 1998), metacognitive knowledge and metacognitive regulation are two distinct components of metacognition. Therefore, they should not be considered interchangeable or similar. For metacognitive knowledge, Flavell (1979) suggested that knowledge of three variables could influence a person’s performance. These variables include: (1) personal variables: knowledge about oneself as a learner, i.e., one’s cognitive strengths, weaknesses, abilities; (2) task variables: knowledge of what kind of information is hard or easy to remember; and (3) strategy variables: knowledge of how to use a strategy, what strategies are available, and how well a strategy works.

In the context of language learning, metacognitive knowledge refers to the general assumptions that students hold about themselves as learners, about factors influencing language learning, and about the nature of language learning and teaching (Victori, 1995). Carrell, Gajdusek, and Wise (1998) highlighted the importance of metacognitive knowledge. If learners are not aware that they lack metacognitive knowledge when their comprehension is breaking down and how they can correct it, strategies introduced by the teachers will fail. Anderson (1991, p. 19) concluded from his research that successful L2 reading comprehension is “not simply a matter of knowing what strategy to use, but the reader must also know how to use it successfully and orchestrate its use with other strategies.” The literature reviewed generally notes that metacognitive knowledge enhances learning outcomes. Lacking metacognitive knowledge, learners may become confused and get lost in the courseware (Governor, 1999).

In Web-based CALL, just as teachers will usually diagnose their students’ level of linguistic proficiency at the outset of a language course, they should also assess their knowledge and beliefs about language learning. Researchers (e.g., Cotterall, 1999; Jacobs & Paris, 1987; Joe & You, 2001; Oxford, 1990; Victori, 1995; Wenden, 1998) suggested that teachers must assess their students’ metacognition in order to help diagnose poor metacognitive skills and intervene to help the student become more strategic and metacognitive, especially in a hypermedia-based environment.
For FL/SL students, Yang (1999, p. 532) explained that “Teachers can remove students’ misconceptions by providing [metacognitive] knowledge or illustrations concerning the nature and process of second language acquisition.” Teachers should also aim to help language learners develop a more reflective and self-directed approach to learning their new language.

2.2. An authoring issue: web page structure

Paolucci’s (1998) authoring-related issue deals with how the links of the hypermedia document should be organized to represent the knowledge of the expert and, at the same time, guide the learning of the student. Although hypermedia-based learning environments are ideal for stimulating higher-order thinking, Paolucci (1998) raised the following questions that need to be addressed: (1) Will learners form better conceptual models using hypermedia or will the richness of the information overload learners and deteriorate the effectiveness and efficiency of learning? (2) Are some knowledge structure schema better than others in facilitating learning in general, and higher-order cognitive skills in particular? (3) Is there a relationship between the hypermedia knowledge-based structure, cognitive style, and the promotion of higher-order cognitive skills?

Paolucci’s (1998) concerns about Web page structures have been supported by several researchers. For instance, Marchionini (1988) pointed out that one of the hypermedia’s most important design features is how information is structured. Tsai (1989, p.11) has also demonstrated that, “Even though users can freely choose their browsing paths, a hyperdocument has an intrinsic structure which is determined by how the nodes are linked together. This intrinsic structure should have some effects on users’ browsing and commenting activities”. This point is similarly noted by Conklin (1987), who concluded that there is no natural topology for an information space. Brown (1998) further explained that good design for one purpose may not be good for the other, and the way the knowledge is structured will affect how much students learn from the hypermedia.

These views about Web page structures have been verified by several empirical studies. For instance, a study by Rasmussen and Davidson (1996) showed a significant interaction effect among hypermedia structures, learning styles (active–reflective), and performance (cited in Paolucci, 1998). Results from a study by Paolucci (1998) demonstrated the need for structuring the WWW technology to meet the cognitive skills and knowledge base requirements of the individual learner. A more extensive experiment by Brown (1998) investigated the effect a WWW document has on the amount of information retained by a reader. He used three structures to test their effects: (1) one long page, (2) a table of contents leading to individual sections, and (3) short sections of text on separate pages with revision questions. Participants read information structured in one of these ways and were then tested on recall of that information. A further experiment investigated the effect of browsing on information retained. The results showed that the single page version was best for recall of facts, while the short sections of text with revision questions led to the most accurate inferences from the material.

Yo (2001) conducted another study investigating the effects of Web page structures and learning styles on learning gain and learning retention for physics concepts. Participants were 116 Taiwanese elementary students. The variations of Web page structure included: linear structure, hierarchical structure, and networked structure. The results showed that the effect of
Web page structure was not significant. Yo (2001) explained that this might be caused by the interference of learners’ learning strategies. It seems that what the students themselves bring to the learning, such as their metacognitive knowledge, plays an important role in the hypermedia-based lessons.

In general, the empirical studies confirmed that the use of Web-based courses as learning systems may not necessarily lead to improved performance. As Paolucci (1998) explained, when “too much” freedom (as in the case of a network schemata) or “not enough” freedom (as in the case of a hierarchical schemata) is provided to the learner, performance may suffer. Brooks, Simutis, and O’Neil (1985) declared that learners may actually be able to process information more effectively if it is presented in a manner that is closely matched by their learning style. For FL/SL learners, various options for Web page structure exist, and usually numerous learning strategies are embedded in the course pages to train the learner’s autonomacy. If Web-based CALL is well structured for the specific learners, it will guide them through various activities to maximize the chances for language learning.

2.3. Recognizing individual characteristics by neural networks

The problem of recognizing individual characteristics is similar to the problem of character recognition because they both involve the classification of a number of features from a potentially infinite number of possible inputs (Mullier, 1999). Researchers (e.g., Castellano, Fanelli, & Roselli, 2001; Mullier, 1999, 2000) also argued that neural networks are a better alternative to other approaches, such as rule-based systems and statistical systems, in classifying learners because of: (l) their pattern recognition ability on imprecise or not fully understood data, (2) their ability to generalize and learn from specific examples, (3) their ability to be quickly updated with extra parameters, and (4) their speed in execution, which makes them ideal for real time applications (Mullier, 1999).

The work of Castellano et al. (2001) indicated that the multi-layer feed forward (MLFF) neural network performed well in similar problems. They used a competitive neural network to address the problem of mining categories of learners with similar interests and attitudes from empirical data coming in the form of questionnaire responses. A learner profile was derived from each cluster by adopting a neural network to perform cluster analysis of questionnaire answers of learners. They employed an MLFF neural network that was trained via a competitive learning algorithm with the ability to adjust the number of clusters as the learning proceeded.

By observing users’ browsing behavior, Mullier (1999) used a constant number of input neurons, determined by experimentation, to recognize users’ browsing patterns such as path, loop, ring, and spike. The hyperspace utilized by the MLFF neural network was conceived of as time shift, which was defined in a hypermedia system by moving from one node to another. A change in time was defined by this transition in terms of user navigation. The inputs of the neural network provided a series of time-shifted inputs. The time relationship was added to the input data by having the input data ranged from zero to one. The closer to one the input, the older the node was. At each time interval the newness of the node decreased by a small amount until it settled back to zero. Mullier’s study showed that the utilization of MLFF neural networks is a possible solution to recognize individual characteristics such as metacognitive knowledge level.
3. Methodology and procedures

This section is divided into three parts: (1) the development of the Web-based English learning system; (2) the development of the MLFF neural network model which assesses automatically learners’ metacognitive knowledge level; and (3) the experiment to investigate the effectiveness of the neural network model and to examine the effect of Web page structures on the assessment.

3.1. Materials

A Web-based English for Science and Technology (EST) learning system (available: http://140.135.93.10/restless) was developed using a Client/Server Architecture, in which the client (learners), the Web server, and the database server access the Internet for browsing and data storage. The courseware was developed using FrontPage, Active Server Page (ASP), and JavaScript. MS-SQL 7.0 was used for database management. The neural network system was developed with Visual Basic.

The courseware was developed from Restless Earth [interactive video program] (Restless Earth, 1992), which introduces plate tectonics, three major types of earthquake (spreading, translation, and subduction), and the methods for assessing earthquakes. Table 1 shows the outline and structure of the course content. Fig. 1 shows the sample screens of the experimental programs.

Three Web page structures were designed: (1) Networked structure. Users can randomly jump to any page in the program (Fig. 2). (2) Hierarchical structure. The pages are categorized into major

| Table 1
Outline and structure of the instructional program – Restless Earth |
<table>
<thead>
<tr>
<th></th>
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</thead>
<tbody>
<tr>
<td>Restless Earth</td>
</tr>
<tr>
<td>I. Introduction [text]</td>
</tr>
<tr>
<td>A. Prologue [text, video]</td>
</tr>
<tr>
<td>B. Plate tectonics [text, video]</td>
</tr>
<tr>
<td>II. Spreading [text, picture]</td>
</tr>
<tr>
<td>A. Spreading in Heimaey [text, video]</td>
</tr>
<tr>
<td>B. Live with Volcanoes [text, video]</td>
</tr>
<tr>
<td>C. Living with the Elements [text, video]</td>
</tr>
<tr>
<td>III. Subduction [text, picture]</td>
</tr>
<tr>
<td>A. Subduction in Japan [text, video]</td>
</tr>
<tr>
<td>B. Live with Volcanoes [text, video]</td>
</tr>
<tr>
<td>C. Disaster [text, video]</td>
</tr>
<tr>
<td>IV. Translation [text, picture]</td>
</tr>
<tr>
<td>A. Translation in California [text, video]</td>
</tr>
<tr>
<td>B. San Andreas Fault [text, video]</td>
</tr>
<tr>
<td>C. Disaster in San Francisco [text, video]</td>
</tr>
<tr>
<td>D. Disaster in Los Angeles [text, video]</td>
</tr>
<tr>
<td>V. Preparing for Earthquakes</td>
</tr>
<tr>
<td>A. Methods of prediction [text, video]</td>
</tr>
<tr>
<td>B. Epilogue [text, video]</td>
</tr>
</tbody>
</table>
categories (Table 1). Users can only navigate between neighboring nodes (Fig. 3). (3) Linear structure. The nodes are arranged linearly. Users can only use [Previous] and [Next] buttons to browse the page (Fig. 4). Although the groups were different in Web page structure, they shared the same content. Moreover, two embedded support devices (ESDs), Glossary and Script, were available for all Web page structures (Figs. 2–4).

3.2. Development of the neural network system

3.2.1. Representing the browsing behavior with a neural network

The neural network model is concerned with assessing learners’ metacognitive knowledge level from a set of data consisting of learners’ browsing behavior. The MLFF neural network in this
The study has three layers: the input layer, the hidden layer, and the output layer (Fig. 5). Each layer comprises a number of neurons.

The input neurons are used to represent the learner’s browsing behavior. Browsing behavior, in this study, includes the usage of ESDs and the navigation between visited/unvisited Web pages. Ideally, the “overall” browsing behavior should be considered. However, due to the unknown length of input, it is impossible and impractical to include “all steps” in sequence in the input layer. That is because the size of each learner’s browsing nodes can be potentially of any length. Therefore, only the statistics of these features are used so that a constant number of input neurons can be obtained. In this research, the input neurons are divided into three types (Fig. 5).

Type-I input neurons are used to reflect the usage ratios of ESDs. The courseware of this study includes two ESD types: Glossary and Script (Figs. 2–4). Glossary is a list of explanations of words
that might be unfamiliar to the subjects. Script provides the transcriptions of the video segments as printed on the computer screen. Each node of the Type-I input neurons represents the usage ratio of one ESD category (Formula (1)). The values of the first type input neurons range from 0 to 1.

Usage ratio of ESD category \( i \) = Frequency of ESD category \( i \)/Frequency of all ESDs, \( i = 1, 2 \)  

\[
\text{Type-I Usage ratios of ESD}
\]

Type-II input neurons are used to represent the time shift, which is defined by Mullier (1999) as the moving from one node to another in a hypermedia system. Basically, each Web page in the system is defined as either “unvisited” or “visited”. An “unvisited” Web page is a page that the learner has never “accessed” and a “visited” Web page is an “old” instructional node that the learner has accessed before. There are four neurons for the Type-II input neurons. The four nodes are used to indicate the ratio of four types of time-shifted inputs. The four types of time-shifted inputs are: (1) from an “unvisited” Web page to an “unvisited” Web page, (2) from an “unvisited” Web page to a “visited” Web page, (3) from a “visited” Web page to an “unvisited” Web page, and (4) from a “visited” Web page to a “visited” Web page (Mullier, 1999). The ratio of each time-shift type is calculated with Formula (2). The values of the Type-II input neurons range from 0 to 1, too.

Ratio of time-shift type \( j \) = Frequency of time-shift type \( j \)/Total time-shift frequency, \( j = 1, 4 \)  

\[
\text{Type-II Ratios of time shift}
\]

Type-III input neuron is used as the bias node. Therefore, there are totally seven nodes in the input layer.

The hidden neurons provide the processing power of the network and the number of hidden neurons affects the neural network’s ability to learn (Masters, 1993). Basically, the more the hidden neurons, the more the network can learn and hence the more it can memorize (Masters,
1993). However, too many hidden neurons can result in over-fitting, where the network memorizes its training data and does not identify only the salient points of the training data that allow it to generalize (Gurney, 1997). Unfortunately, there are no theoretical rules for determining the optimal number of hidden neurons. In this study, the Genetic Algorithm (GA) was used to find an appropriate number of hidden neurons. It will be discussed in Section 3.2.2.

The number of output neurons is directly driven by the problem, in that there is one output in this study: learners’ metacognitive knowledge level.

3.2.2. Training of the neural network

In this study, the GA is used to train the proposed neural network and find an appropriate number of hidden neurons. The GA is a global random search method, which can reduce the extreme value and get global the best solution with a high probability. The following are the searching processes of the GA model (Fig. 6):

![Flowchart of the genetic algorithm.](image-url)
Initialization. Three types with totally 11 genes are used to determine the network parameters. Each gene is represented by one bit in that the length of the chromosome is set to be 11 bits. The first bit represents two transformation functions, the sigmoid function (Formula (3)) and the hyperbolic tangent function (Formula (4)). The next five bits represent the number of hidden neurons, ranging between 0 and 31. The last five bits represent the learning rate for training the neural network. The learning rate is computed with Formula (5) and the possible value is between 0.1 and 10.

\[
f(x) = \frac{1}{1 + e^{-x}},
\]

\[
f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}},
\]

\[
(X/31) \times 9.9 + 0.1, \quad 0 \leq X \leq 31.
\]

Training neural network and computing fitness values. We decode each chromosome and train the neural network that is corresponding to the chromosome. In this study, the fitness function is \( f(x) = 1/RMSE \).

Termination condition. If a chromosome fitness value goes over \( 1/10^{-4} \) or 10 generations, the system will terminate the training processes.

Selection and reproduction. The top five species having the maximum fitness values are selected and reproduced. Each selected species will reproduce \( n \) new species, where \( n = N \times f_i / \sum_{i=1}^{5} f_i \). Here, \( N \) is 20 and \( f_i \) is the fitness value of the selected specie.

Crossover. There are three common crossover methods: one-point crossover, two-point crossover, and mask crossover. In this study, the mask crossover method is used for its better equitable opportunity.

Mutation. Mutation can prevent GAs from falling into local optimum. In this study, the mutation ratio is set to be 0.1, i.e., each new chromosome shall have 1.1 genes \((0.1 \times 11)\) to mutate, and each generation shall have 22 genes \((1.1 \times 20)\) to mutate in average.

3.3. The experiment

The purpose of the experiment is to examine the effectiveness of the neural network model and to study the effect of Web page structures on this issue. The experiment was conducted in Chung Yuan Christian University, Taiwan, during the Spring semester of 2003. This study examined the suitability of the proposed model and the hypothesis that there is no significant difference on assessment of the three Web page structures.

3.3.1. Procedure and data collection

One hundred and forty-six college freshmen were drawn from three different classes of a required course titled Freshman English. All the subjects had familiarity with computer usages and Web page browsing. Prior to the instructional phase of the experiment, all subjects were administered Schraw and Dennison’s (1994) Metacognitive Awareness Inventory (MAI) to measure their metacognitive knowledge level.
The MAI comprises 52 self-report items for measuring adults’ metacognitive awareness regarding (1) knowledge of cognition and (2) regulation of cognition. These items follow the general format “I did such-and-such”. Two experiments conducted by Schraw and Dennison (1994) supported the two-factor model that factors were reliable (α = 0.90) and intercorrelated (r = 0.54) and suggested that the MAI measured metacognitive knowledge reliably. To reduce the verbalization demands for respondents, the Self-report Inventory was converted to a Likert-scale questionnaire. After reading each of the statements in the questionnaire, students respond on a five-point Likert scale: 1, Strongly Disagree; 2, Disagree; 3, Undecided; 4, Agree; and 5, Strongly Agree. Students’ MAI scores were used for later data analysis.

After the MAI survey, the subjects were randomly assigned into three groups according to the Web page structures: networked, hierarchical, and linear. Participation in the whole study involved approximately 60 min of each subject’s time. For each group, the browsing behavior data of around 70% of the subjects (training data) were used for training the network according to the processes discussed in Section 3.2.2. The input data, the browsing behavior of the learner, can be obtained by recording the usage of ESDs and navigation between visited/unvisited Web pages. The output data, the learner’s metacognitive knowledge level, however, can only be obtained by asking the learner to complete the MAI. The remaining subjects were used as the test data to determine the overall success of the neural network. The test data are the same as the training data in that they have known inputs and outputs. They are different from the training data in that they have not been used for training, i.e., the neural network has never seen the test data before.

The mean square errors (MSE) of assessment were used to determine the effectiveness of the neural network. The MSE of assessment is defined as $\sum_{i=1}^{n}(L_a - L_i)^2/n$, where $n$ is the number of test data, $L_a$ is the metacognitive knowledge level of the test data assessed by the neural network, and $L_i$ is the metacognitive knowledge level of the test data obtained by the MAI. The number of subjects, the number of training data, the number of test data, and the MSE of assessment were collected and listed in Table 2.

### Table 2: Experiment data

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Group</th>
<th>Networked</th>
<th>Hierarchical</th>
<th>Linear</th>
<th>Mixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of subjects</td>
<td></td>
<td>50</td>
<td>48</td>
<td>48</td>
<td>146</td>
</tr>
<tr>
<td>Number of training data</td>
<td></td>
<td>35</td>
<td>33</td>
<td>33</td>
<td>100</td>
</tr>
<tr>
<td>Number of test data</td>
<td></td>
<td>15</td>
<td>15</td>
<td>15</td>
<td>46</td>
</tr>
<tr>
<td>Mean metacognitive knowledge level (from MAI survey)</td>
<td></td>
<td>3.16</td>
<td>3.15</td>
<td>3.20</td>
<td>3.17</td>
</tr>
<tr>
<td>MSE</td>
<td></td>
<td>0.010488</td>
<td>0.006323</td>
<td>0.006466</td>
<td>0.00826</td>
</tr>
</tbody>
</table>

*Training data and test data of the Mixed Group were evenly (or randomly) drawn from the three groups.

4. Results and discussion

The mean square errors (MSE) of assessment in Table 2 showed that the assessment errors were small [Networked = 0.010488; Hierarchical = 0.006323; Linear = 0.006466; Mixed = 0.00826] with
respect to the average metacognitive knowledge levels [Network = 3.16; Hierarchical = 3.15; Linear = 3.20; Mixed = 3.17]. Findings suggested that the proposed neural network has performed well and is therefore suitable for assessing the learners’ metacognitive knowledge level.

An ANOVA was implemented to check the effect of Web page structure on assessment errors. Findings show that there is no significant difference among MSEs of these three groups \( F = 0.49909 < \text{critical value} 3.219938 \) (Table 3). Results suggested that the proposed neural network performed equally well in these three Web page structures. The experiment results demonstrated the suitability of the proposed neural network model.

In the context of FL/SL learning, metacognitive knowledge is essential for successful language learning, because language learners are often overwhelmed by too much unfamiliar vocabulary, confusing rules, different writing systems, and social customs. Researchers (e.g., Jacobs & Paris, 1987; Victori, 1995; Wenden, 1998; Yang, 1999) therefore suggested that teachers must assess their students’ metacognition in order to help diagnose poor metacognitive skills and intervene to help the students become more strategic and metacognitive, especially in a hypermedia-based environment. In Web-based CALL, this suggestion seems to be more conclusive when the metacognitive variable interacts with other factors, such as document structure of the Web course. This study proposed a neural network approach to assess learners’ metacognitive knowledge level. The experiment results showed that the proposed neural network performed equally well in three common Web page structures, which are networked, hierarchical, and linear.

There are at least three advantages of using the proposed model to assess learners’ metacognitive knowledge level online. First, the fast execution of trained neural networks makes it possible to assess the student’s metacognitive knowledge level with real-time immediacy. Second, the proposed system can be used to develop adaptive educational systems. The model can assess automatically learners’ metacognitive knowledge level without having students respond to any interview or questionnaire questions prior to learning. In a sense, it makes adaptive learning possible for those who fail to complete any questionnaires prior to learning. Finally, it can be used to assess the metacognitive knowledge level of anonymous students. The proposed model possesses the basic features of computer as summarized by Liu (2000), such as accuracy, real-time immediacy, reliability, and compact storage space. In addition, learners’ online browsing behavior can be further analyzed to tailor the Web-based CALL to individual learners.

However, this system has limitations. First, the proposed model includes the factors of time shift and the usage of Glossary and Script in browsing behavior. In a sense, it is constrained by these two factors. In the further study, more data about learners’ browsing behavior can be included in the inputs, such as link types among Web pages and time-on-task that the student has

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>P value</th>
<th>Critical value</th>
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<td>Between group</td>
<td>0.000168</td>
<td>2</td>
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<td>0.610638</td>
<td>3.219938</td>
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<td>0.000168</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sum</td>
<td>0.007223</td>
<td>44</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( H_1: \text{MSE}_N = \text{MSE}_H = \text{MSE}_L; H_{1A}: \text{MSE}_N \neq \text{MSE}_H \neq \text{MSE}_L; F = 0.49909 < \text{critical value} 3.219938 \). \( \therefore \) cannot reject \( H_1 \).
spent on each Web page. Second, according to Schraw and Dennison (1994), metacognitive knowledge includes three subprocesses that facilitate the reflective aspect of metacognition: declarative knowledge (i.e., knowledge about self and about strategies), procedural knowledge (i.e., knowledge about how to use strategies), and conditional knowledge (i.e., knowledge about when and why to use strategies). This neural network model is limited that it emphasizes learners’ metacongitive knowledge level. For researchers and classroom teachers interested in metacognitive knowledge from a diagnostic perspective, future research can assess learners’ metacognitive knowledge in terms of the subprocesses. Moreover, future research can couple the identified metacognitive knowledge level with adaptive educational hypermedia systems.

5. Conclusion

Learning language through technology has become an important part in applied linguistics (Chapelle, 2001). As a consequence, it is urgent to know the nature of the technology and how the medium can be used to enhance language acquisition. To meet the challenge, this paper presents a neural network model to assess automatically learners’ metacognitive knowledge level by observing his/her online browsing behavior without asking the student to answer any questions or filling out any form. Browsing behavior, in this study, includes the usage of ESDs and the navigation between visited/unvisited Web pages. It is implemented through a multi-layer feed forward (MLFF) neural network. The experiment results verified the suitability of the proposed model and the MSEs of the three groups showed no significant differences with respect to the Web page structures.

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