An Approach for Detecting Students' Working Memory Capacity from their Behavior in Learning Systems*

Ting-Wen Chang[a]; Moushir M. El-Bishouty[a,b]; Sabine Graf[a]; Kinshuk[a]
[a]Athabasca University, Edmonton, Canada
[b]City for Scientific Research & Technological Applications, Egypt
{tingwenchang; moushir.elbishouty; sabineg; kinshuk}@athabascau.ca

Abstract — **Working memory capacity (WMC) is a cognitive trait that affects students' learning behaviors while performing complex cognitive tasks. Knowing students' WMC can positively enhance students' learning in many ways, for example, by providing them with adaptive content and activities to suit their individual WMC. This paper presents an approach for identifying students' WMC from their learning behaviors in learning systems. The approach as well as its implementation into an existing detection tool are introduced in this paper. The following six learning behaviors, extracted from the literature, are modeled to infer students' WMC: linear navigation, constant reverse navigation, performing simultaneous tasks, recalling learned material, revisiting passed learning objects, and corresponding learning styles.**

Keywords: Working Memory Capacity, Student Modeling, Learning System

I. Introduction

Knowing students' cognitive abilities can help in many ways to enhance learning and teaching in learning systems [1][2]. For example, teachers can use this information to provide meaningful recommendations to their students. Furthermore, information about students' cognitive abilities can be used as input for adaptive systems to provide students with customized learning content and activities to suit their individual abilities. In this paper, we focus on the identification of one important cognitive trait for learning, namely working memory capacity.

Working memory capacity (WMC) enables the human brain to keep active a limited amount of information for a very brief period of time [4]. Traditionally, WMC can be measured by a variety of memory span tasks including counting span, operation span, and reading span tasks which are related to the performance in complex cognitive tasks [5][6][7]. However, an obvious disadvantage of such tasks is that students have to do them in addition to their learning. Another disadvantage is that students' WMC is detected at one point of time and any distractions or lack of motivation to conduct this task seriously affects the result.

The aim of this study is to enable typical learning systems to automatically identify different levels (high/low) of students' WMC from their learning behavior and actions in learning systems. This paper introduces an approach and framework which profiles students' behavior and actions from the activity log data available in a learning system's database and identifies behaviors patterns that provide indications for a particular WMC level. These behavior patterns are derived from literature and the respective indications from these patterns are then used to calculate a students' WMC. The proposed approach has been implemented in a detection tool, namely DeLeS [19], which aims at automatically identifying students' learning styles from students' behavior in online courses, resulting in an extended framework for identifying WMC and learning styles. All functionality in the extended framework is developed in a generic way and is applicable for typical learning systems.

The next section presents related works on student modeling approaches and working memory capacity. In section 3, the framework for identifying WMC in learning systems is introduced, including explanations on the preprocessing steps, the relevant behavior patterns for WMC detection, and the calculation of individual WMC from these patterns. Section 4 concludes the paper by providing a summary of the findings and plans for future work.

II. Related Work

A student model is an important part of adaptive learning systems, allowing them to model key aspects of students' characteristics, preferences and needs for providing rich adaptivity [10][11]. Two different student modeling approaches exist for identifying students' characteristics, preferences and needs in learning systems: collaborative and automatic [18]. In the collaborative approach, the student provides explicit data (e.g., learning goals, preferences, etc.) for the student modeling mechanism. The automatic approach refers to building and updating the student model automatically based on the behaviors and actions of students in learning systems. For example, Conati and Maclaren [3] used an automatic approach to analyze students' browsing data recorded in the log file of a web-based learning system and concluded that students' cognitive style (field dependence and independence) and learning behaviors are related. Another example for the use of an automatic approach is provided by Chen [2] who focused on modeling and scaffolding students' cognitive skills related to learning from work-out examples as well as from their exploration activities. Furthermore, Biswas et al. [12] developed a learning system which provides self-regulated learning and metacognitive support from the computer agents and can

* The authors acknowledge the support of NSERC, iCORE, Xerox, and the research related gift funding by Mr. A. Markin.

978-0-7695-5009-1/13 $26.00 © 2013 IEEE
DOI 10.1109/ICALT.2013.29

also automatically identify a range of students' behaviors related to self-regulated learning/meta-cognition. Cognitive trait model (CTM) is another example for an automatic student modeling technique that profiles students according to their three cognitive traits: working memory capacity, inductive reasoning ability, and associative learning skills [8]. The CTM is very much related to our work. While the concept of CTM could be generalized, its implementation has not been that way. In our work, we particularly focus on using behavior patterns that can be identified in any learning system and course, and integrate this concept into a detection tool that can be applicable for learning systems in general.

Several studies have highlighted the importance of WMC for learning and investigated the relations between WMC and different aspects, such as reading comprehension, academic achievement, and attention control [6][13][14]. For example, Carretti et al. [6] concluded that individuals with poor reading comprehension seem to have impaired ability in their WMC to actively maintain relevant information, inhibiting off-goal information and in updating their memory content. Alloway and Alloway's findings [13] showed that a five-years-old child's working memory is a better predicator of academic achievement than IQ. These studies suggest that working memory may be a core cognitive ability that underlies, and constrains, our ability to process information across cognitive domains. In addition, the study by Woehrle and Magliano showed that students with high WMC are better in maintaining attentional focus on a cognitive task when facing multiple distractions over time [14].

III. FRAMEWORK

The DeLeS tool [19] has been developed to analyze log data in different learning systems in order to identify students' learning styles based on the Felder-Silverman learning styles model [20]. In this paper, the framework is extended for automatically detecting not only students' learning styles but also their WMC based on the students' continuous behavior in online courses. The framework consists of two components: the data extraction component and the calculation component, as shown in Figure 1. The data extraction component is responsible for extracting relevant data from the learning system's database, preprocessing these data, and passing the preprocessed data to the calculation component. The calculation component then uses these data to detect patterns from students' behavior (in the Pattern Detector) and calculates students' WMC from the detected patterns (in the WMC Calculator). In the following subsections, a detailed explanation is provided about each step of this framework.

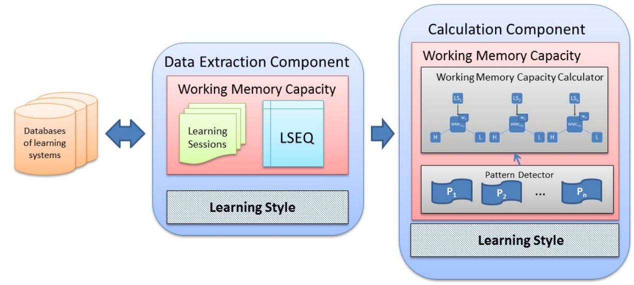

Figure 1. Framework for Identifying WMC

A. Preprocessing of data

In order to analyze students' behavior and detect relevant behavior patterns, some preprocessing of behavior data and course data is required. More concretely, the preprocessing includes three steps:

1) Identifying learning sessions: A learning session is a series of learning activities that a student does while focusing on learning. A learning session typically starts when a student logs in and ends when a student logs out. Furthermore, we additionally consider breaks in learning or simply closing the learning system without logging out. In order to do so, for each learning activity, an upper threshold is predefined by teachers based on the type of activity to indicate the maximum time a student would typically spend on a learning activity. This threshold is used to identify learning breaks based on log data which typically include timestamps of each activity that a student does. Such learning breaks then indicate the end of one learning session and the beginning of a new learning session.

2) Filtering learning activities: When analyzing the behavior patterns of students to infer indications about their WMC, we only focus on learning activities. Therefore, general activities such as a student making modifications to his/her user profile or a user checking his/her marks are not seen as learning activities and are not considered in a learning session. Furthermore, we filter out activities where a learner spent very short time (e.g., because he/she clicked on the wrong link or is searching through pages until he/she finds the page that he/she actually wants to read).

3) Building a learning sequence (LSEQ) table: In order to infer relevant information about students' WMC from their behaviors, a very important aspect is the sequence in which students go through a course in relation to the sequence in which the course is laid out (e.g., do they follow the intended sequence, do they revisit learning objects, etc.). Since the course structure and sequence of learning activities are stored in different ways depending on the learning system and the different database schema that is used in a learning system's database, we extract the information about the sequence in which the course is laid out and store this information in an internal database table called LSEQ table. When a course designer/teacher makes any changes to the course structure in the learning system, the modification time is stored in the internal database. Once the course designer/teacher uses the DeLeS tool to detect students' WMC, this modification time is used to check whether the LSEQ table needs to be updated before using it to calculate students' WMC.

B. Relevant behavior for WMC detection

In learning situations, there are several behavior patterns known in literature that give indications for a student's WMC. In this work, we focused only on behavior patterns that are domain-independent and learning system independent, in order to ensure that the proposed framework can be used for different learning systems. In this research, six patterns are considered, which are explained in the subsequent subsections. Since most of these patterns are based on students' navigational behavior, types of navigational behavior are described by a relation function, *R(preLO, currLO)*. This function relates two learning objects (LOs): the source (*preLO*) and the destination (*currLO*).

1) Linear navigation pattern: Linear navigation means that students learn the materials linearly and follow the learning sequence of the course defined by teachers. Huai [15] performed an experiment to investigate the relationship between WMC, long-term memory and a serial/holistic learning style. To draw conclusions about the relationship between WMC and a serial/holistic learning style, linear and non-linear navigational behavior of students was investigated. As a result, Huai found that students with high WMC tend to focus on linear navigation and students with low WMC tend to use non-linear navigation. A sample of linear navigational behavior is shown in Figure 2. When LO B is learned, and the previous LO of LO B (defined in the LSEQ table), LO A, has been learned before, linear navigation is found, no matter whether other LOs are visited between LOs A and B. If this linear navigation is found, it gives an indication for high WMC. Otherwise, non-linear navigation is found, which gives an indication for low WMC.

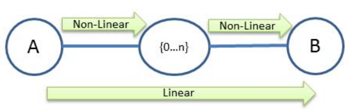

Figure 2. A sample of linear navigational behavior

2) Constant reverse navigation pattern: Reverse navigation means that a student revisits an already visited LO. Constant reverse navigation indicates that a student frequently goes back to an already visited LO. This behavior can be explained by the limited capacity of working memory for students with low WMC [9]. The process of constant reverse navigation is caused by an insufficient WMC to hold on the materials that have just been visited [8]. When the learning materials that a student just read on the previous page should still be fresh in his/her working memory, the constant need to navigate backwards is a sign of working memory deficiency. The definition of constant reverse navigational behavior is that there are more than two LOs revisited in the same learning session and the navigational relations of these LOs are not defined in the LSEQ table (and therefore not in line with the sequence of LOs in the course structure). Figure 3 shows a sample of constant reverse navigational behavior including the following relations of navigation: *R(A, B), R(B, C), R(C, A), R(A, C)*. In these navigational relations, two relations, *R(C, A)* and *R(A, C),* are not defined in the LSEQ table and the two destination LOs, A and C, are revisited. Thus, the constant reverse navigational behavior is found, which gives an indication for low WMC.

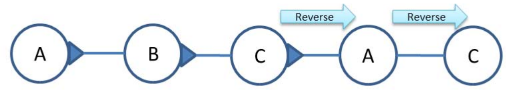

Figure 3. A sample of constant reverse navigational behavior

3) Performing simultaneous tasks pattern: The performing simultaneous tasks pattern is transferred from the ability of attentional control on performing two tasks simultaneously. Previous studies have shown that when performing two tasks simultaneously, low WMC participants were less accurate than participants with high WMC [14][16]. For identifying this pattern, the overlapping navigational behavior is investigated which indicates that a student tries to perform two tasks simultaneously. As shown in Figure 4, if a student visits at least one other LO in between LO A and its evaluation, EA, the overlapping navigational behavior is found. In such situation, the student learns LO A first and then learns other LOs before taking the evaluation of LO A. Therefore, she/he needs to remember the concept of LO A in her/his working memory while learning other LOs. If the student then passes the evaluation of LO A, the simultaneous tasks pattern is found, which gives an indication for high WMC. If she/he fails, the non-simultaneous tasks pattern is identified, which gives an indication for low WMC.

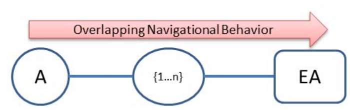

Figure 4. A sample of overlapping navigational behavior

4) Recalling learned material pattern: The recalling learned material pattern is transferred from the relationship between WMC and long-term memory. This pattern is similar to the performing simultaneous tasks pattern but it is identified within two different learning sessions. Prior works have argued that the individials' ability to retrieve information from long-term memory is determined by their WMC [7][16]. As a result, they found that low WMC participants cannot recall as much information from long-term memory as high WMC participants since low WMC individuals do not search the remembered information in their long-term memory as effectively as high WMC individuals. Figure 5 shows a sample of this pattern. This pattern is found if a student visits LO A in one session but does not perform an evaluation of her/his knowledge on LO A in that session. In a different learning session, the student then does not visit LO A but goes directly to the evaluation of LO A (EA). If the student then passes the evaluation, it means that she/he could recall the previously visited information from LO A from her/his long-term memory and the recalling learned material pattern is found, which gives an indication for high WMC. If she/he fails the evaluation, the non-recalling learned material pattern is identified, which gives an indication for low WMC.

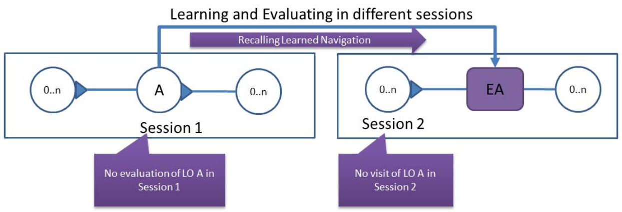

Figure 5. A sample of recalling navigational behavior

5) Revisiting passed LO pattern: Similar to the previous pattern, the revisiting passed LO pattern is transferred from the ability of using WMC to retrieve information from long-term memory. As mentioned in the previous sections, several studies have argued that individuals with low WMC cannot recall as much information from long-term memory as high WMC individuals [7][16]. This pattern considers a situation where a student visited LO A and successfully completed its evaluation (EA) in the same session but then revisits LO A aftewards in a different learning session. In such case, the student seems to have problems recalling information from his/her long-term memory and wants to reread some of the already learned information. The more time the student spends on LO A during revisit, the more problems the student seems to have in recalling the respective information from the long-term memory and therefore, the stronger the indication for low WMC is. In order to calculate this pattern, we consider the time the student i spent on LO A in order to pass the evaluation as base value b_i, and the time that the student i spent when he/she revisits LO A as value v_i. Furthermore, let r_i be the ratio v_i/b_i, representing how much time a student spent on revisiting LO A in relation to how much time she/he spent to learn this LO. Let r_{avg} be the average ratio of all students, calculated based on formula 1 and representing how much time on average each student spent on revisiting LO A in relation to how much time she/he spent to learn this LO.

$$r_{avg} = \frac{\sum_{i=1}^{n} r_i}{n} \quad (1)$$

where n is the overall number of students. This average ratio r_{avg} is then used as threshold and compared to a student's r_i value. If r_i is greater than r_{avg}, the time the student took for reading and recalling already learned information is above average and therefore indicates low WMC. On the other hand, if r_i is smaller than r_{avg} the time the student took for reading and recalling already learned informaiton is below average and therefore indicates high WMC. If r_i is equal to r_{avg}, an indication for average WMC is given.

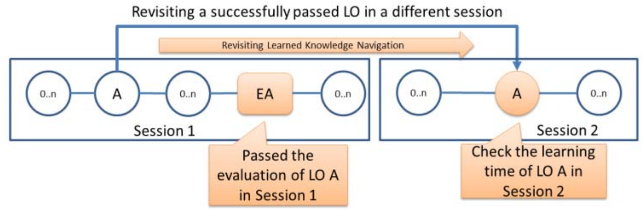

Figure 6. A sample of revisiting navigational behavior

6) Learning style pattern: The learning style pattern is based on the relationship between learning styles and working memory capacity. While there are several studies that conclude findings that hint for an indirect relationship between learning styles and WMC (a summary is provided in [21]), Graf et al. [10] investigated the direct relationship between WMC and the four learning style dimensions of the Felder-Silverman learning style model (FSLSM) [20], namely the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimensions. The results of the study showed that students with a reflective or intuitive learning style tend to have high WMC and students with an active or sensing learning style tend to have low WMC. For the visual/verbal dimension, the study found only a one-directional relationship, namely that learners with a verbal learning style tend to have high WMC, whereas visual learners have either high or low WMC. No relationship for the sequential/global dimension was found. The learning style pattern considers these relationships. Accordingly, if a student has an active or sensing learning style, this gives an indication for a low WMC. On the other hand, a reflective, intuitive, or verbal learning style gives an indication for a high WMC. An average value of all indications from a student's learning styles is calculated and this value represents the overall indication of WMC for this learning style pattern.

C. *From patterns to WMC*

After extracting and preprocessing data in the data extraction component, these data are then passed on to the calculation component, which is responsible for calculating the students' WMC based on the five navigational behavior patterns and the learning style pattern. If a navigational behavior pattern is detected in a relation between two LOs, this relation is considered as an activated relation for the particular behavior. In each learning session, a value is calculated for each of the five navigational behavior patterns based on the number of activated and non-activated relations in this session. This value shows how strongly the student's behavior represents the respective pattern. Subsequently, each value is transferred to its indication for WMC (e.g., a high value for linear navigation provides an indication for high WMC). Then, the indications from the five navigational behavior patterns and the indication based on the learning style pattern are summed up and divided by the number of activated patterns (where the learning style pattern is considered as activated as soon as the learning styles of the student are known). The result of this calculation represents the indication for WMC of the respective session. Although the learning style pattern is not dependent on learning sessions, we decided to add the indication from this pattern in each session in order to ensure that this pattern has the same impact in the detection process as all other navigational behavior patterns.

Each learning session also contains a weight, which determines the influence of each session on the overall value of WMC and is calculated based on the number of activated relations in a session for all patterns. In order to calculate the student's WMC, the WMC indication of each session is multiplied by the weight of the respective session. Subsequently, the results for all sessions are summed up and divided by the number of sessions. The resulting value is the identified WMC for the respective student.

IV. CONCLUSIONS AND FUTURE WORK

This paper proposed an approach for identifying students' WMC from their activity log information in learning systems, as well as its implementation into the detection tool DeLeS [19]. Six behavior patterns have been identified to be, on one hand, relevant for the identification of WMC as concluded by the literature, and on the other hand, to be domain and learning system independent so that our proposed approach is generic and can be used in different learning systems.

As identified in several studies, students' different levels of WMC can affect students' learning performances [11][13][14]. The information about students' WMC can be helpful to support students in many ways. For example, by making students and teachers aware of the different WMC levels, teachers can individually support students and provide them with personalized recommendations, while students can better understand their weaknesses and strengths, and use this information to improve their learning. Furthermore, information about students' WMC can be used as input for an adaptive learning system to automatically provide students with individualized materials and activities as well as personalized recommendations, considering their WMC.

Our future research will deal with using the identified information about students' WMC to provide teachers with recommendations for improving their course design and providing individualized support for learners.

REFERENCES

[1] P. D. Antonenko and D. S. Niederhauser, "The influence of leads on cognitive load and learning in a hypertext environment," Computer in Human Behavior, vol. 26, no. 2, 2010, pp. 140-150.

[2] L.-H. Chen, "Web-based learning programs: Use by learners with various cognitive styles," Computers & Education, vol. 54, no. 4, 2010, pp. 1028-1035.

[3] C. Conati and H. Maclaren, "Empirically building and evaluating a probabilistic model of user affect," User Modeling and User Adapted Interaction, vol. 19, no. 3, 2009, pp. 267–303.

[4] G. A. Miller, "The magical number seven, plus or minus two: Some limits on our capacity for processing information," Psychological Review, vol. 63, 1956, pp. 81-97.

[5] J. M. Broadway and R. W. Engle, "Lapsed attention to elapsed time? Individual differences in working-memory capacity and temporal reproduction," Acta Psychologica, vol. 137, no. 1, 2011, pp. 115-126.

[6] B. Carretti, E. Borella, C. Cornoldi, and R. D. Beni, "Role of working memory in explaining the performance of individuals with specific reading comprehension difficulties: A meta-analysis," Learning and Individual Differences, vol. 19, no. 2, 2009, pp. 246-251.

[7] N. Unsworth, T. S. Redick, J. Gregory, J. Spillers, and G. A. Brewer, "Variation in working memory capacity and cognitive control: Goal maintenance and microadjustments of control," The Quarterly Journal of Experimental Psychology, vol. 65, no. 2, 2012, pp. 326-355.

[8] T. Lin, Kinshuk, and A. Patel, "Cognitive trait model – a supplement to performance based student models," Proc. of international conference on computers in education, 2003, pp. 629–632.

[9] S. Graf, T. Liu, Kinshuk, N.-S. Chen, and S.J.-H. Yang, "Learning styles and cognitive traits – Their relationship and its benefits in web-based educational systems," Computers in Human Behavior, vol. 25, 2009, pp. 1289-1289.

[10] M. C. Desmarais and R. S. J. Baker, "A review of recent advances in learner and skill modeling in intelligent learning environments," vol. 22, 2012, pp. 9-38, doi 10.1007/s11257-011-9106-8.

[11] A. Marengo, A. Pagano, and A. Barbone, "Adaptive learning: A new approach in student modeling," Proc. of the ITI 2012 34th International Conference, Information Technology Interfaces (ITI), IEEE Press, Jun. 2012, pp. 217-222, doi:10.2498/iti.2012.0450.

[12] G. Biswas, H. Jeong, J. Kinnebrew, B. Sulcer, R. Roscoe, "Measuring self-regulated learning skills through social interactions in a teachable agent environment," Res. Practice Tech. Enhanced Learning, vol. 5, no. 2, Jul. 2010, pp. 123-152, doi: 10.1142/S1793206810000839.

[13] T. P. Alloway and R. G. Alloway, "Investigating the predictive roles of working memory and IQ in academic attainment," Journal of Experimental Child Psychology, vol. 106, 2010, pp. 20–29.

[14] J. L. Woehrle and J. P. Magliano, "Time flies faster if a person has a high working-memory capacity," Acta Psychologica, vol. 139(2), 2012, pp. 314-319.

[15] H. Huai, "Cognitive style and memory capacity: effects of concept mapping as a learning method," Doctoral Dissertation, Oct 2000, Twente University, The Netherlands.

[16] R. W. Engle, "Role of working-memory capacity in cognitive control," Current Anthropology, Working Memory: Beyond Language and Symbolism, vo. 51, no. 1, Jun. 2010, pp. 17-26.

[17] J. Cantor and R. W. Engle, "Working memory capacity as long-term memory activation: An individual differences approach," Journal of Experimental Psychology: Learning, Memory and Cognition, vol. 19, 1993, pp. 1101-1114.

[18] P. Brusilovsky, "Methods and techniques of adaptive hypermedia," User Modeling and User-Adapted Interaction vol. 6(2-3), 1996, pp. 87-129

[19] S. Graf, Kinshuk, T.-C. Liu, "Supporting Teachers in Identifying Students' Learning Styles in Learning Management Systems: An Automatic Student Modelling Approach, " Educational Technology & Society, Vol. 12 (4), 2009, pp. 3-14.

[20] R. M. Felder and L. K. Silverman, "Learning and teaching styles in engineering education," Enginerring Education, vol. 78, 1988, pp. 257-285.

[21] S. Graf, T. Lin, Kinshuk, "The relationship between learning styles and cognitive traits - Getting addtional information for improving student modelling, " Computers in Human Behavior, Vol. 24, (2), 2008, pp. 122-137.