Expertise Measure for Dynamic Task Selection within Intelligent Educational Systems

François Courtemanche, Mehdi Najjar and André Mayers

ASTUS Research Group, Department of Computer Science, University of Sherbrooke, Canada

f.courtemanche@usherbrooke.ca; andre.mayers@usherbrooke.ca

Interdisciplinary Research Center on Emerging Technologies, University of Montreal, Canada

mehdi.najjar@usherbrooke.ca

Abstract

This paper presents a task selection model for personalised educational instruction. The proposed model is based on the student expertise level and it takes into account performance and mental load in order to adapt task selection. The article also discusses distinctions between our approach and related works.

1. Introduction

Hitherto, most intelligent educational systems rely on performance or mastery measures to tailor pedagogical behaviour [1,3,10]. Several researches in educational psychology advocate that highly effective instructional conditions can only be achieved by personalising instruction regarding the learner expertise level [5,9]. This paper introduces a novel approach for task selection within intelligent educational system (IES) which use the student expertise level. The approach is based on a well-known formal definition of expertise which takes into account performance and mental effort [9]. While other researchers use empirical subjective methods to assess mental effort [2,4,7], the originality of our approach resides in the automatic continuous non-subjective estimation of mental load and performance during problem solving. The remainder of the paper is organised as follow. In section 2, we expound the main architecture of our IES. Section 3 describes the learning task classification regarding the curriculum, followed by explanations about the performance (section 4) and the mental load (section 5) calculation mechanisms. Section 6 explains how these measures are used in order to tailor task selection. Concluding remarks are given in section 7.

2. The IES architecture

Similarly to most Intelligent Educational Systems [12], our IES architecture includes four main modules. Figure 1 shows an overview of the architecture.

![Figure 1 – The architecture](image)

The expert agent is able to dynamically solve any problem given to a student and its main role is to provide optimal solutions to problems. The interface agent is the link between actions carried out in the virtual learning environment by the student and the other modules of the architecture. The interface agent main function is to connect the interactions made in the virtual environment with the domain knowledge. The learner agent encodes the student knowledge and his behaviour (actions). In addition, our learner agent is responsible for modeling the characteristics of the mental effort (cognitive load) of the student during learning activities using a working memory simulator. The pedagogical agent provides educational remediation in response to the learner behaviour. Aside to these main modules, the laboratory resources contain the learning tasks and the domain knowledge of the virtual labs expressed in terms of semantic and procedural knowledge. Information concerning the learner expertise level is stored in the learner resources.
3. Curriculum and task classification

The virtual laboratories in our IES are attached to a curriculum specifying their learning objectives (LO). The latter are defined as skills to be mastered with regards to their priority level. A skill is defined as a set of procedures needed to its achievement. The laboratories domain knowledge is designed in order to express the different LOs.

The learning tasks contained in the laboratory resources are created in order to manipulate the learning objectives. Each learning task is defined by particular difficulty levels regarding the different skills involved in its LOs. This classification is used to implement a more fine-grained task selection algorithm (see section 6.1).

4. Performance assessment

In order to have a precise and useful expertise measure for task selection it is important to proceed to a detailed and accurate performance assessment. During problem resolution, the learner agent collects information concerning the performance level for each skill manipulated by the student. The following equation is used to perform this assessment.

\[
\text{Performance}_{\text{skil}} = \frac{\text{Final Result} \times \text{Solution Quality}}{\text{Execution Time}}
\]

Our learning objective performance equation incorporates the three often used performance measures [4]. The final result concerns the correctness of the skill’s output. The solution quality is measured as the distance between the learner solution and the optimal solution provided by the expert agent. This distance is defined as the difference in procedures selection with regard to the optimal sequence. The execution time of the skill is provided by the interface agent which keeps track of the beginning and the end of the manipulations needed to perform the skill. After each problem, the learner agent evaluates the student performance regarding the different LOs. This measure is combined to the learner performance history in order to select the next learning task (see section 6.1).

5. Mental load estimation

During an instructional session, mental load originates from the interaction between task and learner characteristics. This section explains how mental load is estimated according to the cognitive load theory.

5.1. The Cognitive Load Theory

The cognitive load theory (CLT) is a framework dedicated to the identification of optimal methods of instruction [8,9]. CLT is based on the interaction between the information structures and the human cognitive processes during the performance of complex cognitive tasks.

Cognitive load is a construct defined by three components: intrinsic cognitive load (ICL), extraneous cognitive load (ECL) and germane cognitive load (GCL). ICL represents the interaction between the knowledge to be learned and the expertise level of the learner. It is affected by the number of elements to be addressed simultaneously in working memory during problem solving. ECL represents all form of load which is not directly devoted to the execution of the current task (e.g. interface manipulations, attention switching). This load is not effective for learning and can be reduced by a better instructional design. GCL represents the load resulting from learning processes (automation, schema acquisition). It is a form of extraneous load that actively participates in learning. These three types of cognitive load are additives. Their sum may not exceed the working memory capacity without causing a failure of the ongoing task or severely impairing learning [8].

Several experimental methods exist to evaluate cognitive load [6]: subjective methods, psychophysiological techniques and the secondary-task techniques. Most approaches using cognitive load scores for task selection purposes rely on subjective methods as rating scales to assess mental effort [2,4,7]. Our IES implements a novel analytical estimation method for mental load using a working memory simulator. This approach intends to be more detailed, less intrusive and to leads to a more fluent learning experience.

5.2. Cognitive load estimation

During the execution of a learning task, the interface agent identifies which knowledge elements are being manipulated via the virtual laboratory interface. At each resolution step, the learner agent operates a working memory simulation using the knowledge instances handled by the student and his expertise level (prior knowledge). The cognitive load resulting from skill execution is then estimated with the working memory simulator. This analytical estimation is done automatically during problem resolution avoiding, therefore, the burden of subjective evaluation after each problem.
6. Task selection

In the IES literature there are four basic methods for task selection: student choice, fixed order, mastery learning and macroadaptation [11]. Our tutoring system implements a form of macroadaptation relying on student expertise level. In macroadaptation, the tutoring system knows which knowledge components are exercised by a task and estimates the student’s mastery degree of these knowledge components [11]. Instead of the knowledge mastery level, our approach uses an expertise measure for macroadaptation task selection.

After each task resolution, the learner agent evaluates the involved learning objectives (LO) regarding performance and mental load measures defined in the two last sections. A non-mastered LO with the highest priority is chosen as the discriminator for task selection. A new task with the proper difficulty variation for this learning objective is selected for the next problem to be solved by the student. Table 1 illustrates the jump size selection rule for learning objective difficulty.

<table>
<thead>
<tr>
<th>Mental Effort</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0 0 0 +3 +4 +5 +6</td>
</tr>
<tr>
<td>2</td>
<td>0 0 0 +2 +3 +4 +5</td>
</tr>
<tr>
<td>3</td>
<td>-2 -1 0 +1 +2 +3 +4</td>
</tr>
<tr>
<td>4</td>
<td>-3 -2 -1 0 +1 +2 +3</td>
</tr>
<tr>
<td>5</td>
<td>-4 -3 -2 -1 0 +1 +2</td>
</tr>
<tr>
<td>6</td>
<td>-5 -4 -3 -2 0 0 0</td>
</tr>
<tr>
<td>7</td>
<td>-6 -5 -4 -3 0 0 0</td>
</tr>
</tbody>
</table>

Table 1 – Jump size selection table

The jump size table is based on the one defined by Corbalan & al. [4]. It is adapted in order that the selected next task difficulty varies only regarding one discriminating learning objective. For instance, a performance score of 5 associated with a mental effort of 3 for a particular LO yields a difficulty jump of 2 for this learning objective. The others LOs difficulty levels for the next task stay the same in order to foster learning of one skill at the time. This fine-grained task selection model leads to a more flexible and precise student adapted learning.

7. Conclusion

We have proposed a model for task selection within IESs that uses expertise measure in order to dynamically adapt instruction to the learner expertise level.

8. References