Informing the Detection of the Students' Motivational State: an Empirical Study

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Abstract. The ability to detect the students' motivational state during an instructional interaction can bring many benefits to the performance of an Intelligent Tutoring System (ITS). In this paper we present an empirical study which provided us with a considerable amount of knowledge regarding motivation diagnosis. We show how this knowledge was formalised in order to create a set of motivation diagnosis rules that can be incorporated into a prototype tutoring system. We also briefly present how these motivation diagnosis rules were evaluated in another study.

1 Introduction

Many tutoring systems attempt to motivate the student by using multimedia, games, etc. This approach seems to be based on the idea that it is possible to create instruction that is motivating *per se*. However, as Keller mentions in [6], it is not always the case that if the instruction is of good quality motivation will follow. There has been some previous work that has dealt explicitly with motivation in ITSs (e.g.[4, 5, 9]), but these have dealt mainly with instructional planning, and not so much with motivation diagnosis. We believe that there is a pressing need for more research in this area [2], and we focus in this paper on how to elicit and formalise knowledge to diagnose the student's motivational state during an interaction with an instructional system.

The issue of how human teachers detect their students' motivation has been virtually unexplored in AI and Education research. Introspection and observational studies could throw some light into this issue, but they may be of limited usefulness for motivation diagnosis in ITSs. In a traditional instructional setting or any other social interaction there is a vast amount of information available through various communication channels, such as facial cues, posture, etc. [1], and there has been some interesting research on incorporating some of these cues in instructional systems (e.g. [10]). But many such cues that help us detect other people's emotions (or motivation) are perceived unconsciously, which makes it difficult to elicit emotion (or motivation) detection knowledge.

In order to limit the amount of sources of information available for knowledge elicitation, we designed a study in which a tutor is asked to infer a student's motivational state. But in order to do so, the only information that is available to her[1] is the pre-recorded screen interaction of a student with an instructional system. That is, the tutor

[1] In this paper there are two main characters: the participants of the study, and the students whose interactions with an instructional system were replayed. In order to facilitate readability we use

is only able to see on a computer screen the interface of the instructional system which the student was manipulating. We expected that it would be easier for tutors to rationalise their motivation diagnosis knowledge in this setting than if they were presented, say, with video-recordings of tutoring interactions. At the same time, we believed that the knowledge inferred in this way would be easier to formalise in terms of information available to the instructional system (such as the duration of the interaction with the system, mouse movements, etc.).

2 Background on recorded interactions

As explained above, the participants of this study watched a number of recorded interactions of a student with a prototype ITS for learning Japanese numbers. This prototype ITS (MOODS) is a simple tutoring system with an added motivation self-report facility. This means that the student is able to report about his perceived motivational state during the interaction with MOODS. As a result of a previous study [3], we had a number of recorded interactions with the system, which were used as the basis for the study presented in this paper.

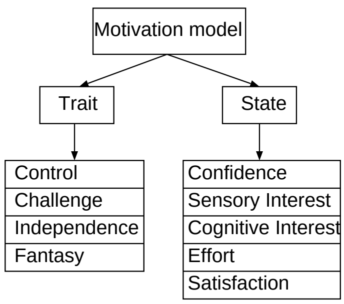

Fig. 1. Motivation model

The self-report facility available in MOODS is based on a motivation model which is presented in figure 1[2]. The model is based on the relevant literature (e.g. [6–8]) and it is composed of a number of motivational factors, which are divided in two classes: trait variables, or 'permanent' characteristics of the student; and state variables, or more 'transient' characteristics. Definitions for all these variables are given in table 1.

The trait variables in our motivation model are: control, challenge, independence and fantasy. There seems to be agreement on the importance of control and challenge for student's motivation. Fantasy, although not often included in theories of motivation

female pronouns to refer to the study participant and male pronouns to refer to the students. This has no relation to their actual gender.

[2] A more detailed description can be found in [3].

Variable	Definition
Control	Refers to the degree of control that the student likes having over the learning situation (i.e. does he like to select which exercises to do, in which order, etc. rather than let the instructor take these decisions?).
Challenge	Refers to the degree that the student enjoys having challenging situations during the instruction (i.e. does he like to try difficult exercises that represent a challenge for him?).
Independence	Refers to the degree that the student prefers to work independently, without asking others for help (i.e. does he prefer to work on his own, even if he finds some difficulties, and try to solve them by himself rather than asking for collaboration or help from others?).
Fantasy	Refers to the degree that the student appreciates environments that evoke mental images of physical or social situations not actually present (i.e. does he like the learning materials being embedded in an imaginary context?).
Confidence	Refers to the student's belief in being able to perform the task at hand correctly.
Sensory interest	Refers to the amount of curiosity aroused through the interface presentation (i.e. appeal of graphics, sounds, etc.).
Cognitive interest	Refers to curiosity aroused through the cognitive or epistemic characteristics of the task (i.e. regardless of the presentation issues, does the student find the task at hand cognitively appealing?).
Effort	Refers to the degree that the student is exerting himself in order to perform the learning activities.
Satisfaction	Refers to the overall feeling of goal accomplishment (i.e. does the student think that the instruction is satisfying and that it is getting him closer to his goals?).

Table 1. Definitions of motivation model variables

in Education, seems to be a factor that can play an important role in engaging the student (e.g. [8]). Independence, as defined in table 1, is related to challenge, but also to interpersonal motivations, such as: cooperation, competition and recognition [8].

The state variables represent transient characteristics of the student that relate to the material being learned. In figure 1 the state variables are presented in a more or less 'chronological' order. Thus, considerations of how confident he feels about succeeding in the task will likely take place before engaging in the task. This, together with the interest (both sensory and cognitive) that the lesson arouses in him, will influence the effort that he will put into the task. Satisfaction, as defined in table 1, represents the overall feeling of goal accomplishment, and will be influenced by all the variables above, plus by the outcomes of the task [6].

3 Materials

The participants of this study were asked to watch the recorded interactions of a student with MOODS, and they were asked to infer and comment on the motivational state of the student during the interaction. For this, we developed A_MOODS, which can be used to replay the actions of a previous student interaction with MOODS and to predict his motivational state. The A_MOODS interface can be seen in figure 2.

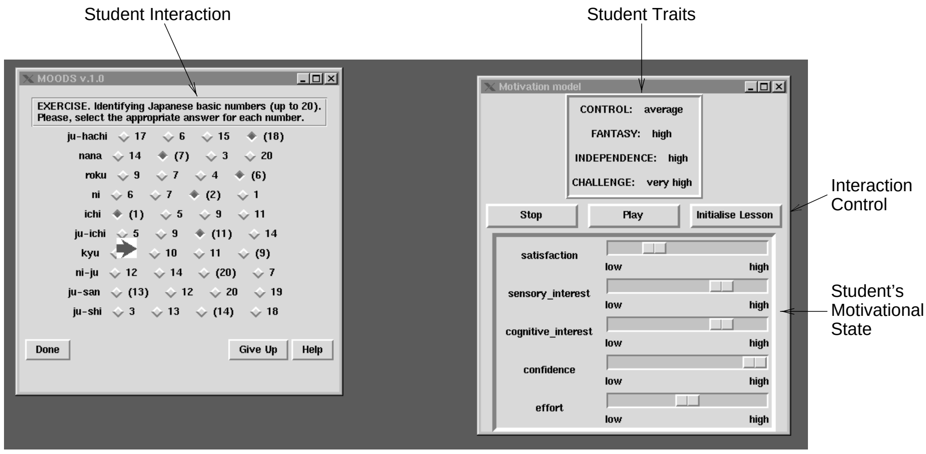

Fig. 2. A_MOODS interface.

The actions made by the student are replayed in the window to the left (with title MOODS v.1.0). To facilitate the viewing of the student interaction, an arrow (around the centre of the window in figure 2) indicates the mouse movements.

The window to the right (titled Motivation model) consists of three frames.

1. The top frame is a representation of the *student traits* of the motivation model (described in section 2). The values for these were obtained through a questionnaire during the self-report study described in [3].
2. The three buttons in the middle of the window control how the student interaction is replayed.
   – The replay of the student interaction starts when *Play* is pressed, and stops when *Stop* is pressed.
   – The button *Initialise Lesson* allows the user to 'rewind' the interaction to the beginning of the current lesson.
   – The replay of the interaction is done in real time, except for the replay of the theory lessons. In this type of lesson there is very little student activity, and therefore the system simply shows a message regarding how long the student took to learn the lesson[3]. After this the interaction continues.
3. The bottom frame is a representation of the student's *motivational state*, as discussed in section 2 (The task of the participants for this study was to predict the likely values of these motivational variables as the instruction replay took place).

[3] A sample message of this type is: "The student used 147 seconds to study this lesson".

In order to let the participants update the student's motivational model, the interaction stops by default in any of the following three situations:

1. When the student presses any of the buttons (Done, Give Up, or Help), but before any feedback is given by the system.
2. After feedback is presented to the student.
3. When a new lesson is presented to the student.

In these cases a small message[4] is shown to remind the participant to update the motivational model. If the participant does want to update the motivational model or comment on any aspect of the instruction at any other time, she can stop the interaction by pressing the *Stop* button.

4 Methodology

For this study 10 post-graduate students with previous teaching and/or tutoring experience volunteered to participate. After reading the study instructions, the interaction with A_MOODS started. The interaction can be summarised as follows:

1. The participant was given information about the trait characteristics of a student.
2. Then she was shown a replay of the student's interaction with MOODS.
3. Throughout the interaction, and particularly at any stop points, the participant was encouraged to give verbal comments on the student's motivational state and the possible factors affecting it.
4. Whenever the interaction was paused the participant was asked to update the motivational state if she had enough information to make an inference. And she was asked to verbalise the reasoning behind her inferences.
5. When the student pressed any of the three buttons available (Done, Give up, or Help), the participant was also encouraged to comment on the type of feedback that she thought would be the most appropriate to give to the student at that moment.

Throughout the duration of the study, the participant's comments were recorded on an audio disc, and were later transcribed and analysed.

5 Results

Before the study started, most of the participants commented on the perceived difficulty of the task. They expected not to be able to make any inferences based on the information provided. Contrary to their expectations, most of the participants made a considerable number of reasoned inferences about the student's affective state, and at the end of the study they commented that the task was actually not so difficult and that there was quite a lot of information available to them in order to perform these inferences.

On average, the time participants spent with the system was around 36 minutes. In this time, an average of 4 lessons were covered, and 8.5 inferences were made per participant. In total we collected 85 inferences. The excerpt below illustrates the type of comments that participants made during this study.

[4] "Please update the motivational model. Afterwards press 'Play' to continue."

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Interviewer:
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And [...] why do you think he is satisfied at this point?
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Participant:
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Well, [...] he is hovering the mouse over the answers each time, he wasn't
randomly moving the mouse, he is looking for the answer, [...] and that he
didn't take a long time to answer the questions. To me that would suggest
that the task is interesting enough to complete with some attention and to
do it properly, if you like. [...]  So, I would increase the satisfaction
here, just for the fact that he did it with confidence.
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Inferred rule from excerpt. Based on the excerpt above, we were able to elicit the rule presented in figure 3. Because the mouse movement through the interface is not random, the participant could infer that the student was paying attention to the task and because it was performed quickly, she inferred that he was confident. And given that:

1. He was interested in the task
2. He was confident
3. He performed the task well

the participant could infer that the student would be highly satisfied. The dashed arrow and the box in figure 3 represent another rule, but serve to illustrate that performing a task quickly can also mean lack of interest, but it is the combination of other evidence that can lead us to believe that, in this case, a quick performance was due to high confidence.

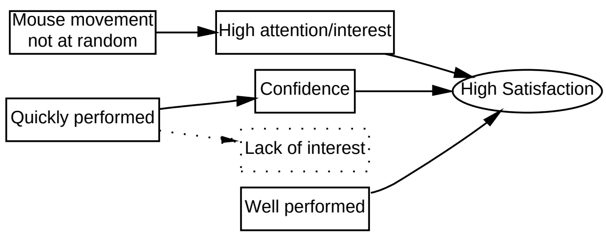

Fig. 3. Inference rule from excerpt.

Elicited motivation diagnosis rules. By analysing all the recorded interviews with participants, we elicited 85 rules similar to that in figure 3. Given a rule, we consider its *inputs* the factors on which the inference of that rule is based. For example, *inputs* to the rule in figure 3 are *Mouse movements*, *Quickly performed*, *Confidence*, etc. The *output* of the rule is its conclusion: *High Satisfaction* in the case of figure 3.

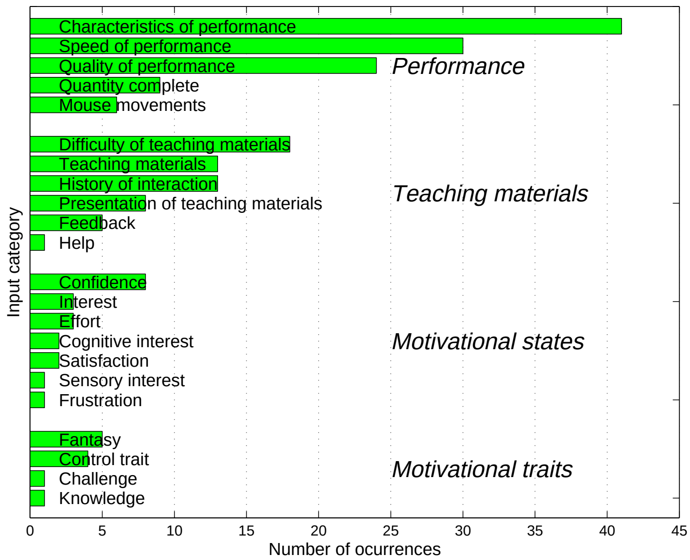

Fig. 4. Occurrences for each input category.

In figure 4 we analyse the elicited rules according to their *input* categories. As we can see, the input factors more often mentioned by the participants were those related to students' performance. The main category in figure 4 is that of *Characteristics of performance*, which was mentioned in 41 out of the 85 provisional rules elicited. This category includes a number of characteristics which relate to the way a student performed during the interaction, such as the order in which he did the exercises, whether he gave up or not, etc.

The second most mentioned broad *input* category was that of *Teaching materials*, in which we include subcategories such as the *Difficulty of the teaching materials*, issues regarding the *History of the interaction*, etc. Although not mentioned as often as *Performance* or *Teaching materials* issues, it can be seen in figure 4 that the student's *Motivation model* and his *Motivational traits* were also considered on a number of occasions as input factors for some of the inference rules.

In figure 5 we can see which output categories were mentioned most often by the participants. Not surprisingly, since this was the main purpose of the study, most of the inference rules have as their *output* a category relating to student's *Motivational model*. But we can see that there were also a number of cases where the *output* of some of the rules was related to other categories. For example, there were some rules in which the participants reasoned about the student's knowledge on the subject, about the feedback that should be provided to the student, etc.[5]

[5] It is interesting to note that some of the results of this study contrast with those of the self-report study mentioned earlier [3]. Thus, participants in this study made fewer inferences about student's effort than about his satisfaction. On the other hand, participants of the self-report

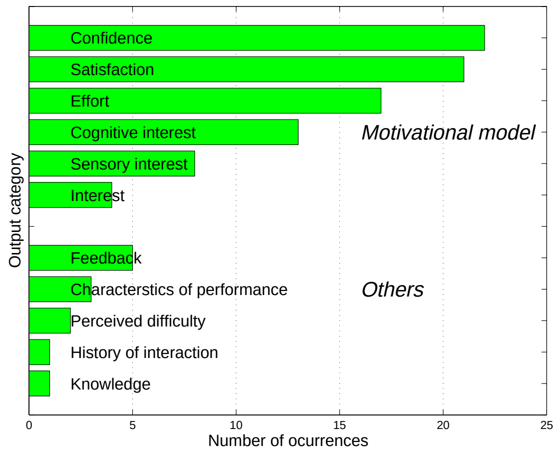

Fig. 5. Occurrences for each output category.

Due to lack of space we cannot present here the complete set of rules inferred from this study, but by way of illustration we present in table 2 some of the rules related to the detection of the factor *Satisfaction*. Each rule has a reference code in the first column of the table (starting with the letters *IS* for the rules that infer a high satisfaction value and starting with the letters *DS* for the rules that infer a low satisfaction value).

Each column represents an *input* factor, which are presented into the same broad categories as in figure 4. The different factors[6] given as input for the rules are:

- Performance
  - **Quality**. Correctness of the answers provided to the exercises.
  - **Speed**. Time spent in doing the instructional unit.
  - **Give up**. Whether the student chose to give up the lesson or not.
- Teaching Materials
  - **Difficulty**. Level of difficulty of the current exercise.
  - **pre(Diff)**. Level of difficulty of the previous exercise.
  - **Control**. Level of control available in the current lesson.
  - **Feedback**. Characteristics of the feedback provided (*Enc*: Encouragement).
- Motivation model
  - Value of the corresponding factor in student's motivational model.
- Motivation traits
  - Value of the corresponding factor in student's motivational traits model.

study reported their effort on more occasions that their satisfaction. A similar situation arises with the factors *Cognitive interest* and *Sensory interest*.

[6] The complete set of rules has a larger number of input factors, but they are not listed here as they were not mentioned for the sample rules given in table 2.

	PERFORMANCE			TEACHING MATERIALS				MOTIVATION MODEL			MOT. TRAITS	
	Quality	Speed	Give up	Pre(Difficulty)	Difficulty	Control	Feedback	Confidence	Effort	Cognitive interest	Control	Output
IS1	High							High		High		High
IS3	High						Enc					Inc
IS4	High						Enc			High		High
IS5										High		High
IS7	High	Fast		X	>X							Inc
IS9						High					High	High
DS1	Low							Low	Low			Low
DS2	Avg		Yes									Low
DS4		V. Slow										Dec
DS7						V. Low					High	Dec

Table 2. Sample diagnosis rules

6 Discussion and further work

As mentioned earlier, participants in this study were initially quite convinced that the task would prove extremely difficult and that it would be virtually impossible for them to extract any useful information about student's motivational state without being able to see him. But despite the original doubts of most participants, we have seen that we were able to infer a large number of motivation diagnosis inference rules.

More importantly, by only showing them the student's interaction with the tutoring system, these rules are based on very concrete aspects of the interaction, such as mouse movements, quality of performance, etc., which can be easily detected in a tutoring system. On the other hand, we believe that if the participants had been able to see the student himself, many of the inferences about his motivational state would have been based on their gestures, posture, etc., which would prove much harder to detect in a regular tutoring system.

This study offered us some clues as to which aspects of the instruction seem to be the most relevant in order to detect students' motivational state, and it provided us with a promising amount of motivation diagnosis rules. But the validity of these rules remains to be analysed. Cross-participant comparison does not seem to be an appropriate way to validate the given set of rules, as the number of rules elicited is not large enough to provide a sufficient number of rules which can be applied under the same conditions. Also, comparison with the self-report study presented in [3] is not appropriate becausethere is no reason to believe that the self-report is necessarily accurate, as 'false' readings can be given under certain circumstances. For example, if the student is too engaged, he would probably forget to update the motivational model. Also, it is likely that students will attempt to 'please' the tutoring system by providing artificially positive readings of their motivation [11].

Therefore, we evaluated these rules by performing another study in which participants were presented with an instructional interaction context and were asked to rate the rules that could be applied under those conditions. This study gave us a chance to find which rules from the current set are generally accepted as valid, and which ones are not. We will be reporting this study shortly.

In conclusion, we can say that the results of this study suggest that it is feasible to infer motivation diagnosis knowledge based only on the information provided by the computer interaction with a tutoring system. We have managed to gather a considerable number of motivation diagnosis rules, although the validity of these has to be proven yet, which we plan to do in a further study.

Acknowledgements

We thank Jeff Rickel, Kaśka Porayska-Pomsta, Thomas Segler, Ben Curry, Manolis Mavrikis and anonymous reviewers for useful comments on previous versions of this paper. This research was partially supported by grant PG 30660835, Ministerio de Educación y Cultura, Spain.

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