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A Framework of Generating Explanation for Conceptual Understanding based on 'Semantics of Constraints'

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Abstract: A framework for indexing problems is proposed, based on which explanation generation and problem sequencing for conceptual understanding in science can be automatized. It helps student learn how to make appropriate models to solve problems and prevents them from superficially read the solution of a worked example and apply it wrongly to others. The results of a preliminary experiment is also described in which the explanations generated based on the framework promoted subjects' conceptual understanding in mechanics.

Keywords: science education, problem practice, worked example, explanation generation, semantics of constraints

1. Introduction

In problem practice in science (e.g., physics), most students fail to acquire the ability to make an appropriate model for a given task. An expert can model not only the behavior of a system in question, but also she/he can do so in various tasks. Such expertise includes identifying the structure of the system in question and the applicable principles/laws for making the necessary and sufficient model. It also includes understanding how/why a model changes when the task is changed. We call such ability 'conceptual understanding' of the domain.

In order to reach such understanding, students need to learn (1) to infer the structural features of problems from the superficial features, and (2) to apply appropriate principles/laws to structural features to make models. For assisting students, it is insufficient to explain how each problem is solved. It must be explicitly explained why the principles/laws are applicable to the given situation (surface structure) and what physical meaning (physical structure) they imply. It is also important to explain how the model changes when the situation (problem) is changed. Furthermore, it would promote such learning to provide students with an appropriately designed and sequenced set of problems (Scheiter and Gerjets, 2003; VanLehn and van de Sande, 2009).

In this paper, we propose a framework for indexing problems, based on which explanation generation and problem sequencing mentioned above can be automatized. In our framework (called 'Semantics of Constraints: SOC'), making a model in physics is regarded as a process in which various constraints (applied principles/laws and modeling assumptions) are imposed on the target system and its behavior. A model is regarded as the set of constraints.

After introducing the SOC framework, we show the method for generating SOC-based explanations. The results of preliminary experiment are also described which proved the usefulness of our framework.

2. Semantics of Constraints and Explanation Generation

Given a physics problem, one makes a model of the target system which is necessary and sufficient for answering the query by embodying an appropriate part of the domain theory. Domain theory consists of a set of propositions each of which describes a principle/law, its applicable condition and resulting constraint(s) on the attribute(s) of the system. Constraints by embodied principles/laws are called the 'constraints of physical phenomenon (PPCs).' In making a model, various modeling assumptions are set. Modeling assumptions define the structure/behavioral range of a system and physical phenomena to be considered. Since an embodied PPC is valid under some modeling assumptions (applicable conditions), a PPC always has its corresponding modeling assumptions. Constraints by modeling assumptions are called the 'constraints of modeling assumptions (MACs).' Boundary condition of a system is given by the 'constraints of boundary condition (BCCs).' They define the influence from the outside of the system. Making the influence which can't/needn't be calculated with a model means defining the boundary of the model (i.e., what physical processes are considered/ignored). That is, a BCC always has its corresponding modeling assumptions. In our framework, a model is the union of PPCs, MACs and BCCs. Especially, though MACs are usually implicit, they are essential for explaining models because MACs gives the validity of PPCs and BCCs. When MACs are changed, PPCs and BCCs also qualitatively change. In order to make a model correctly, therefore, it is necessary to understand the physical meaning of the constraints based on modeling assumptions (i.e., why an assumption is set and what role it plays). More detail about SOC is discussed in Horiguchi and Hirashima (2009), and Horiguchi, Hirashima and Forbus (2012).

A model-making process (i.e., solution) is described as the procedure in which principles/lwas are applied in turn to the given situations (represented with MACs and BCCs) to yield new consequences (represented with PPCs). The explanations about a problem and the difference between problems are generated based on such a representation and the comparison between representations. Such explanations are called ‘SOC-based explanations.’

3. Preliminary Experiment

We conducted an experiment to evaluate the usefulness of our framework. The purpose was to examine whether the SOC-based explanation promotes students' conceptual understanding, that is, whether their representation of problems was improved and they became able to solve various types of problems by using correct models.

Subjects: 15 graduates and under graduates whose majors are engineering participated.

Procedure: First, subjects were given problem set 1 (15 problems in mechanics called PS-1) and asked to group the problems into some categories based on some kind of 'similarity' they suppose, then asked to label each category they made (called 'categorization task 1'). Then, they were asked to solve 8 problems in PS-1 (called 'pre-test'). After a week, the subjects were divided into two groups: the 'control group' (7 subjects) and the 'experimental group' (8 subjects). The average scores of both groups in pre-test were made equivalent. The subjects in control group were given the *usual explanation* about the solutions of 11 problems in PS-1 (which explains the calculation of the required physical amount from the given ones) to learn. The subjects in experimental group were given the SOC-based explanation about the same problems as the usual explanation to learn. Then, by using problem set 2 (other 15 problems in mechanics called PS-2), 'categorization task 2' was conducted in the same way as above. Finally, subjects were asked to solve 8 problems in PS-2 (called 'post-test').

Measure: The quality of the representation of problems was measured with the categories, their 'frequencies' (number of problems accounted for) and the time required in each categorization task. The ability to solve various types of problems was measured with the scores in each test. The effect of learning with usual/SOC-based explanation was measured with the comparison of the results of two categorization tasks and pre-/post-tests. The superiority of SOC-based explanation to usual explanation was measured with the differences of improvement of categorization and problem-solving between experimental and control groups.

Results: The categories made by subjects and their frequencies in categorization task 1 are shown in table 1. Most of the subjects categorized the problems based on the similarity of their superficial features, such as the components of the system (e.g., inclined plane), the figures of motion (e.g., circular motion). Additionally, all subjects finished the task within 10 minutes. The results of categorization task 2 are shown in table 2 (control group) and table 3 (experimental group). Many subjects of control group still categorized the problems based on the similarity of their superficial features, while many subjects of experimental group became to categorize the problems based on the similarity of their structural features, that is, the dominant principles/laws of problems (e.g., Newton's second law, balance of forces, conservation of energy). Additionally, all subjects of control group finished the task within 10 minutes again, while the subjects of experimental group required from 25 to 35 minutes. These results suggest the learning with SOC-based explanation promoted representing problems based on their structural features rather than their superficial features (the increase of the time required suggests the subjects of experimental group inferred the physical structure from surface structure). The average scores in pre- and post-tests are shown in figure 1 (in both tests, full marks were 52). In pre-test, there was no significant difference of average scores between groups (control group: 36.0 and experimental group: 33.6, t-test $p > .10$). In post-test, though there was also no significant difference of average scores between groups (control group: 42.7 and experimental group: 47.6, t-test: $p > .10$), the increase of average score of experimental group was larger than that of control group. This result suggests the learning with SOC-based explanation promoted the ability to solve various types of problems, that is, to make appropriate models regardless of their superficial features. These results suggest that SOC-based explanation about the solution of problems and their differences can assist students in reaching conceptual understanding.

Table 1: Categories in task-1

	Number of subjects using category labels (N_1=15)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1 \times N_2$ =225)	Number of problems wrongly accounted for (N^*=225)	Number of problems correctly accounted for ($N^C=N-N^*$)
Springs	**12**	**3.1**	**37**	**2**	**35**
Free fall etc.	**9**	**4.1**	**37**	**2**	**35**
Collision	**12**	**2.0**	**24**	**0**	**24**
Circular motion	**12**	**1.9**	**23**	**1**	**22**
Acceleration	**3**	**5.7**	**17**	**1**	**16**
Strings	**7**	**2.0**	**14**	**0**	**14**
Inclined planes	**5**	**2.2**	**11**	**0**	**11**
Balance	5	2.4	12	4	8
Object only	1	5.0	5	0	5
Friction	3	1.7	5	0	5
Second law	2	2.5	5	2	3
Pulleys	1	2.0	2	0	2
Balance of energies	1	4.0	4	2	2
Motion of weight	1	2.0	2	0	2

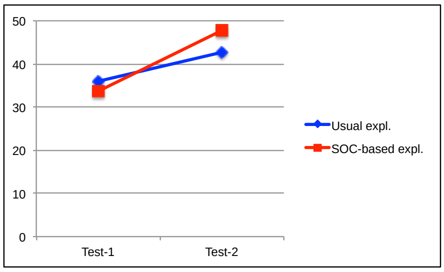

Figure 1. Average scores of tests.

Table 2: Categories in task-2 (usual)

	Number of subjects using category labels (N_1=7)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1 \times N_2$ =105)	Number of problems wrongly accounted for (N^*=105)	Number of problems correctly accounted for ($N^C=N-N^*$)
Springs	**4**	**4.5**	**18**	**0**	**18**
Inclined planes	**4**	**3.3**	**13**	**0**	**13**
Balance of forces	**3**	**3.7**	**11**	**0**	**11**
Conservation of energy	3	6.0	18	9	9
Second law	3	3.7	11	2	9
Pulley and string	2	3.5	7	0	7
Circular motion	4	1.5	6	0	6
Pendulum	3	1.7	5	0	5
Simple harmonic motion	2	2.0	4	1	3
Collision	2	1.0	2	0	2

Table 3: Categories in task-2 (SOC)

	Number of subjects using category labels (N_1=8)	Average size of category (N_2=15)	Number of problems accounted for ($N=N_1 \times N_2$ =120)	Number of problems wrongly accounted for (N^*=120)	Number of problems correctly accounted for ($N^C=N-N^*$)
Balance of forces	**7**	**4.4**	**31**	**5**	**26**
Second law	**7**	**3.6**	**25**	**1**	**24**
Conservation of energy	**8**	**4.1**	**33**	**12**	**21**
Linear accelerated motion	3	3.3	10	2	8
Conservation of momentum	3	1.3	4	1	3
Acceleration	1	3	3	0	3
Springs	1	3	3	0	3
Pulleys	1	3	3	0	3
Simple harmonic motion and period	2	1	2	0	2
String and tension	1	2	2	0	2
Time	1	2	2	0	2

4. Conclusion

We showed the explanations generated with the SOC framework could promote conceptual understanding through a preliminary experiment. SOC-based explanation generator can provide a basic function for designing various instructional methods (e.g., a detailed explanation is gradually simplified (scaffolding-fading), a sequence of problems is given which promotes spontaneous induction).

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