DOCUMENT RESUME

ED 475 760 TM 034 881

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TITLE	Assessment Applications of Ontologies.
PUB DATE	2003-04-00
NOTE	23p.; Paper presented at the Annual Meeting of the American Educational Research Association (Chicago, IL, April 21-25, 2003).
PUB TYPE	Reports - Descriptive (141) -- Speeches/Meeting Papers (150)
EDRS PRICE	EDRS Price MF01/PC01 Plus Postage.
DESCRIPTORS	*Authoring Aids (Programming); *Computer Software; *Concept Mapping; *Educational Assessment
IDENTIFIERS	*Domain Knowledge; Knowledge Maps; *Ontology; Riflery

ABSTRACT

This paper discusses the use of ontologies and their applications to assessment. An ontology provides a shared and common understanding of a domain that can be communicated among people and computational systems. The ontology captures one or more experts' conceptual representation of a domain expressed in terms of concepts and the relationships among the concepts. The ontology standardized the terms and structures of the domain. The paper presents two examples of the use of ontologies for assessment purposes. The first example describes than application for the domain of rifle marksmanship, and the second example discusses the use of ontologies in the design of authoring systems to link assessment, content, and cognitive demands. The overall purpose for developing the ontology of rifle marksmanship was to capture the knowledge and structure of the domain in a way that allows the exploration of the use of ontologies for assessment and instructional purposes. In the other example, the ontology was developed to use as a domain template against which to score knowledge maps. The technology behind ontologies has matured to the point that computational tools are readily available. An ontology-based authoring system can impose structure on the authoring task and check that user-specified values simultaneously satisfy all constraints among the assessment components. (Contains 28 references.) (SLD)

ASSESSMENT APPLICATIONS OF ONTOLOGIES

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Paper presented at the annual meeting of the
American Educational Research Association, Chicago, IL, April 2003

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ASSESSMENT APPLICATIONS OF ONTOLOGIES[1]

In this paper we discuss the use of ontologies and their applications to assessment. The work reported herein is part of parallel efforts to explore the feasibility and utility of ontologies. The first application discussed is embedded in a larger research program to develop assessment models and tools for Naval distributed learning. CRESST is under contract to the Office of Naval Research and the first application of our work is to U.S. Marine Corps (USMC) marksmanship training. Our USMC work is focused on developing online assessments of Marines' knowledge of rifle marksmanship. The second application discussed is embedded in a larger research program to develop online assessment design and delivery tools for middle school science teachers.

In each case, ontologies are used as a computational structure to capture explicit representations of knowledge, whether the knowledge is content-focused (e.g., rifle marksmanship or physics), or assessment design-focused (e.g., assessment design principles). In both cases ontologies are key components in the development, delivery, design, and scoring of assessments.

Definition of an Ontology

An ontology provides a shared and common understanding of a domain that can be communicated among people and computational systems (Fensel, Wahlster, Lieberman, & Hendler, 2003). The ontology captures one or more experts' conceptual representation of a domain expressed in terms of concepts and the relationships among the concepts. An ontology is a commitment to a point of view of how a domain is structured but there can be multiple representations (Chandrasekaran, Josephson, & Benjamins, 1999; McGuinness, 2003). Ontologies are important because they provide a common, explicit framework for sharing and using knowledge. More concretely, an ontology standardizes the terms and structure of the domain. The standardization makes possible sharing of the ontology–and thus the knowledge contained therein–for use across multiple computer platforms for different applications (Gruber, 1995).

[1] The work reported herein was supported under the Educational Research and Development Centers Program, PR/Award Number R305B960002, as administered by the Office of Educational Research and Improvement, U.S. Department of Education, Office of Naval Research Award Number N00014-02-1-0179, as administered by the Office of Naval Research, and the National Science Foundation Award Number REC-0129406. The findings and opinions expressed in this report do not reflect the positions or policies of the National Institute on Student Achievement, Curriculum, and Assessment, the Office of Educational Research and Improvement, the U.S. Department of Education, the Office of Naval Research, or the National Science Foundation.

Ontologies were first developed as part of the AI research effort to facilitate knowledge sharing and reuse. The use of ontologies has extended recently to fields such as information retrieval, knowledge management, medical guidelines, military, and e-commerce. CRESST is now applying ontologies to assessment.

Ontologies to Support Assessment and Instruction

For assessment and instructional purposes, the capability to express the concepts in a domain, the links among the concepts, and the governing constraints offers clear advantages over relational or highly structured data models. It is often the case that the representation of a domain is best represented as network (vs. a strictly hierarchical representation, for example), especially in knowledge-rich applications.

The existence of computational tools to create, edit, maintain, and exchange ontologies makes feasible the use of ontologies in assessment and instruction. For example, Protégé, originally developed in 1987 at Stanford University, is in its third generation (Gennari et al., 2002). Protégé has an easy-to-use graphical user interface, Java implementation, and an active developer community. Similar products are available from both academic and commercial vendors.

At CRESST, we are implementing ontologies for a variety of applications related to assessment:

- To capture the structure of a domain
- To capture experts' representation of a domain
- To encode and bind content to a domain structure
- To score knowledge maps
- To package and deliver content at different grain sizes
- To be part of a recommender system
- To provide a structure to guide the automated design of assessments

In addition, we are evaluating the potential of ontologies to assist in the creation of assessments on-the-fly (e.g., dynamic generation of terms and links for the CRESST knowledge mapper depending on the current state of the examinee's knowledge).

In the following sections, we present two examples of how we are using ontologies for assessment purposes. In the first example we describe an application for the domain of rifle marksmanship. In the second example, we discuss the use of ontologies in the design of authoring systems to link assessment, content, and cognitive demands. We believe ontologies and assessment objects support the rapid development of an assessment authoring system and ultimately, through use of the authoring system, result in higher quality assessments developed by end-users (e.g., teachers).

Example 1: Ontology of USMC Rifle Marksmanship Knowledge

We have developed an ontology of rifle marksmanship as part of our work with the U.S. Marine Corps. One aspect of this work was to capture the knowledge related to rifle marksmanship. The overall purpose for developing an ontology was to capture the knowledge and structure of the domain in a way that would allow us to explore the use of ontologies for assessment and instructional purposes. We judged the domain of rifle marksmanship to be an ideal candidate to represent in an ontology because the domain is bounded and there was agreement among the domain experts about the important topics. A secondary purpose was packaging the knowledge for potential use by the Marine Corps training command.

Our research questions with respect to ontologies are related to investigating how ontologies can be used to support (a) the automated scoring of knowledge maps, (b) the conceptual searching of information, and (c) given performance information on different assessments, the generation of individualized recommendations of relevant information that could fill in an individual's knowledge gaps.

Domain Structure

Our knowledge engineering strategy was to capture knowledge in two representations: (a) as outlined by doctrine (e.g., USMC field manuals), information which could be organized as a hierarchically structured body of knowledge; and (b) as perceived by experts (e.g., coaches, snipers, rifle team members), information which could be organized conceptually (i.e., as a network) to reflect how domain experts perceived the knowledge to be interrelated.

Currently, our rifle marksmanship ontology contains 168 different concepts that cover seven fundamentals of rifle marksmanship and 160 relationships among the concepts using 16 relationship types. Figure 1 shows a portion of the hierarchy of the ontology. The structure of the content is captured by the *Knowledge* class. The hierarchical structure shows the taxonomy of class and subclass relationships among the topics.

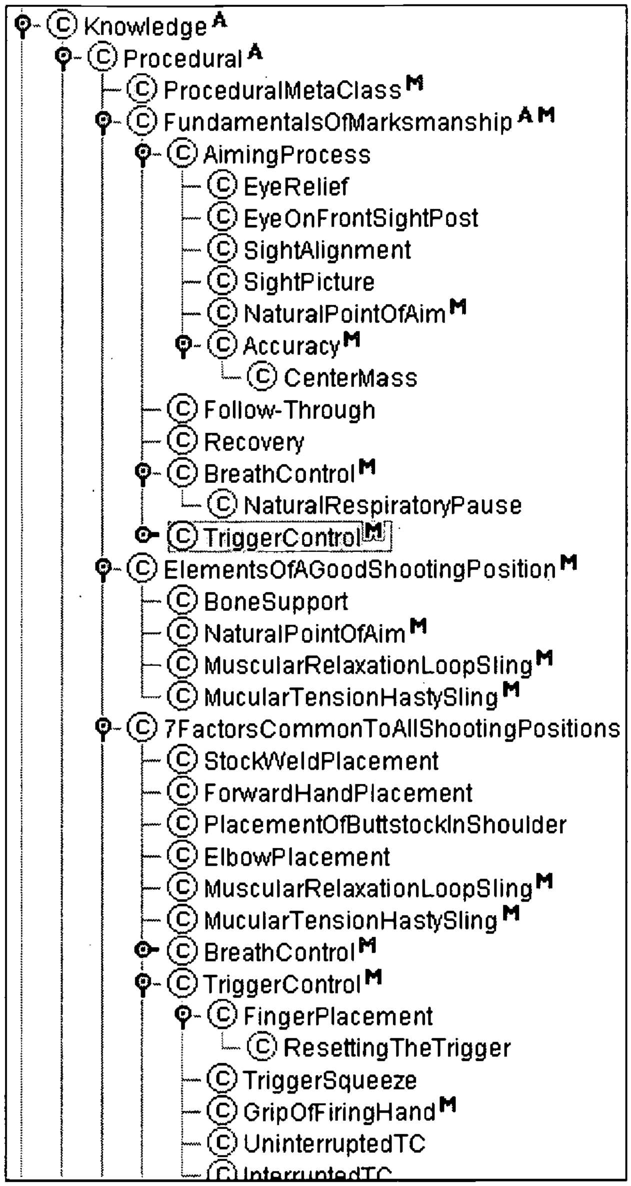

Figure 1. Example of the rifle marksmanship content organized hierarchically.

Figure 2 shows how the content is organized as perceived by our domain experts. In this case, the organization is a network and represented by the *Relationship* class. The *Relationship* class is made up of subclasses that represent high-level relation types (e.g., causal, part/whole). Subclasses of each relation type represent increasingly specific relations (e.g., *PartOf* is a particular kind of relation within the *PartWhole* class). The right pane in Figure 2 shows specific instances of the *PartOf* relation that directly connect different topics shown in Figure 1. A visual representation of the set of relations is shown in Figure 3. Our assumption is that the hierarchical representation reflects the organizational structure of the content similar to a table of contents, and the relational structure captures the detailed relations that presumably underlie deep understanding of the content. The significance of this distinction will become apparent when we describe how the ontology is used for scoring knowledge maps, semantic searching, and recommending relevant content.

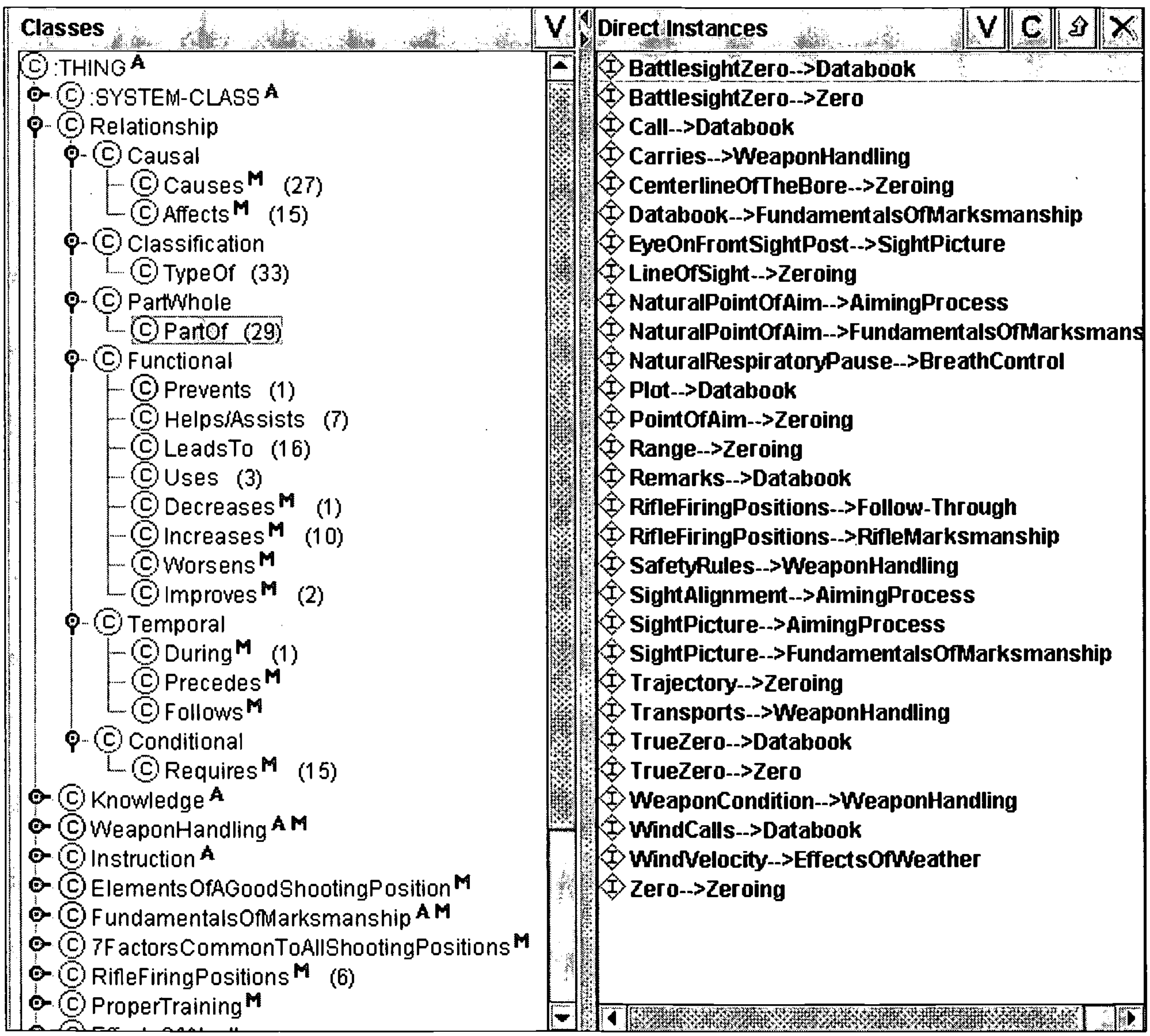

Figure 2. Example of relationship classes. The relationship class specifies how the content is related conceptually.

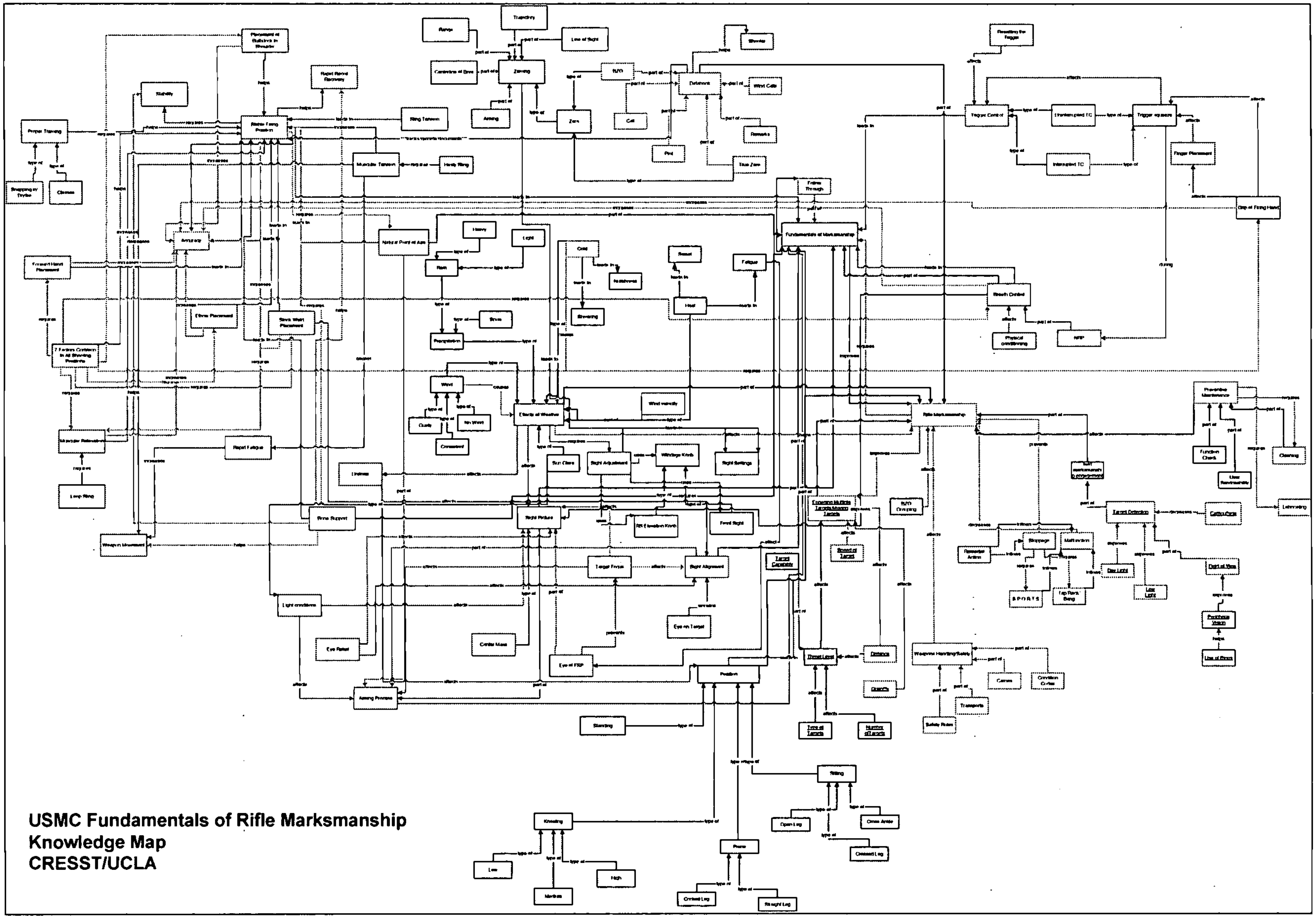

Figure 3. Composite expert map that is captured in the ontology *Relationship* class.

Binding Content to the Ontology Structure

Many ontologies typically capture only the structure of the domain (e.g., Figure 1). However, to be useful instructionally, content would ideally be bound to the structure. For example, Figure 4 shows an example of how content is related directly to objects in the ontology. For each topic, we have defined different knowledge types—conceptual (or declarative) knowledge and procedural knowledge. Further, we have partitioned the information into subtypes: definition, explanation (i.e., why the topic is important), and elaboration (i.e., supplemental information). Although not shown in Figure 4, we have also allowed for the inclusion of different media types (e.g., video, picture, URL). For example, for the topic *BreathControl* we have a video demonstrating the effects of breathing on the position of the rifle muzzle and bullet strike (breathing causes the rifle to move vertically; firing while breathing results in a vertical dispersion of shots).

Source material was drawn from the U.S. Marine Corps rifle marksmanship manual (USMC, 2001). Marksmanship training is derived from this manual. For concepts, the instructional content is delineated in terms of definition, explanation, elaboration, and multimedia examples (e.g., a picture of the trigger) where appropriate. For relations, the instructional content was an explanation of why the particular relation holds under the particular conditions.

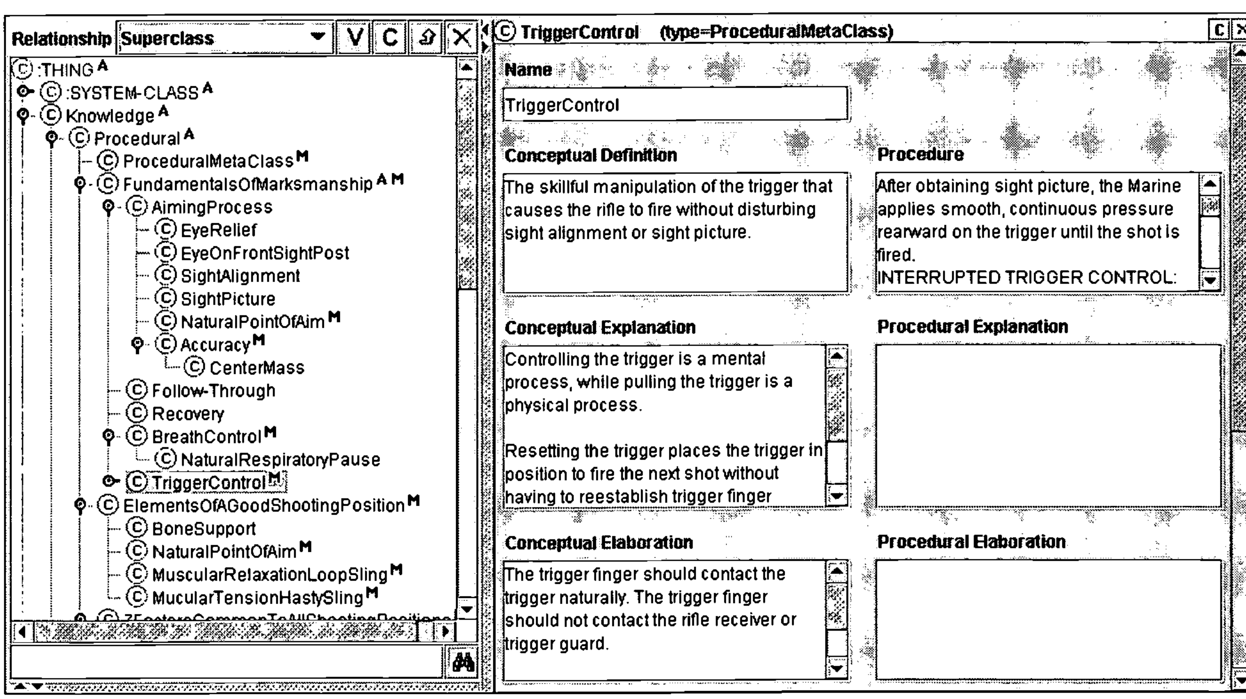

Figure 4. Example of the rifle marksmanship content bound to the topic *TriggerControl*.

Ontology Application: Automated Scoring of Knowledge Maps

We have developed automated methods of scoring knowledge maps in our prior work based on comparing students' knowledge maps to a criterion map (e.g., Chung & Baker, 1997; Chung, Harmon, & Baker, 2001; Chung, O'Neil, & Herl, 1999; Herl, Baker, & Niemi, 1996; Herl, O'Neil, Chung, & Schacter, 1999; Klein, Chung, Osmundson, Herl, & O'Neil, 2002; Lee, 2000; Osmundson, Chung, Herl, & Klein, 1999). One shortcoming of this approach is that the score is a count (i.e., the number of propositions [node-link-node tuple] in the student's map that are also in the criterion map). An alternative approach is to score each proposition on a scale. This approach yields information on the degree of accuracy of the proposition (e.g., Osmundson et al., 1999; Ruiz-Primo, Schultz, Li, & Shavelson, 2001).

Several studies have investigated the technical properties of scoring knowledge maps. For example, Ruiz-Primo et al. (2001), in addition to scoring knowledge maps proposition-by-proposition, also scored students' maps against a criterion map. The correlation between the proposition accuracy score and expert-based score was sufficiently high for Ruiz-Primo et al. to conclude that an expert-based method was the most efficient scoring method (i.e., in terms of scoring time and reliability of scores). Similar results were found by Osmundson et al. (1999) and Chung et al. (2001).

The findings of Ruiz-Primo et al. (2001) are consistent with earlier work by Herl (1995), Herl et al. (1996), and Osmundson et al. (1999). In general, scoring student knowledge maps using expert-based referents has been found to discriminate between experts and novices (Herl, 1995; Herl et al., 1996), discriminate between different levels of student performance (Herl, 1995; Herl et al., 1996), relate moderately to external measures (Aguirre-Munoz, 2000; Herl, 1995; Herl et al., 1996; Klein, Chung, Osmundson, Herl, & O'Neil, 2002; Lee, 2000; Osmundson et al., 1999), detect changes in learning (Chung et al., 2001; Osmundson et al., 1999; Schacter, Herl, Chung, Dennis, & O'Neil, 1999), and be sensitive to language proficiency (Aguirre-Munoz, 2000; Lee, 2000).

Given the expressive potential of ontologies and the utility of knowledge mapping as an assessment task, one capability we are currently implementing is using the ontology as a domain template against which to score knowledge maps. Domain expert maps can easily be captured and folded into the ontology via the *Relationship* class (Figure 2). Similarly, propositions that are scored individually can also be folded in. By integrating both methods, both the expressive power of the ontology and the scoring potential are increased.

Ontology Application: Recommending Individualized Instructional Content

Because of how we have structured the ontology (i.e., hierarchical and network/conceptual representations) *and* because we have bound content at different grain sizes to specific topics in the ontology, we now have the means to deliver content at different grain sizes depending on the application. In this section we describe our technique for identifying knowledge gaps and delivering individualized content.

Identifying knowledge gaps. The first step in recommending individualized content is to identify an individual's knowledge gaps. Once the gaps are identified, relevant content needs to be retrieved and delivered to the individual.

Identifying what students do and do not know is accomplished by diagnostic assessments. For example, our strategy for assessing Marines' understanding of rifle marksmanship is to use a range of measures that reflect different cognitive demands. For example, we broadly sample their knowledge of basic definitions of major ideas (via selected response matching), their cause-effect knowledge of how different aspects of shooting relate to each other causally (via constructed-response knowledge maps), their skill at diagnosing improper shooting positions (via QuickTime VR), and their capability to fix any improper positions identified (via QuickTime VR).

This assessment information is then fused together using Bayesian networks to yield probabilities on the degree to which a Marine understands different topics of rifle marksmanship. A Bayesian inference network, also known as an influence or probabilistic causal network, depicts the causal structure of a phenomenon in terms of nodes and relations (Jensen, 2001). Nodes represent states, and links represent the influence relations among the nodes. Node states can be observable or unobservable.

The utility of a Bayesian inference network is that it yields the probability that an unobservable variable is in a particular state (e.g., understands trigger control) given observable evidence (e.g., knowledge map score). The probability of the unobservable variable being in a particular state is the inference made about student understanding. Figure 5 shows the Bayesian network that depicts presumed knowledge dependencies. Observable nodes are omitted for clarity; however, in general, the leaf nodes would have observables linked to them.

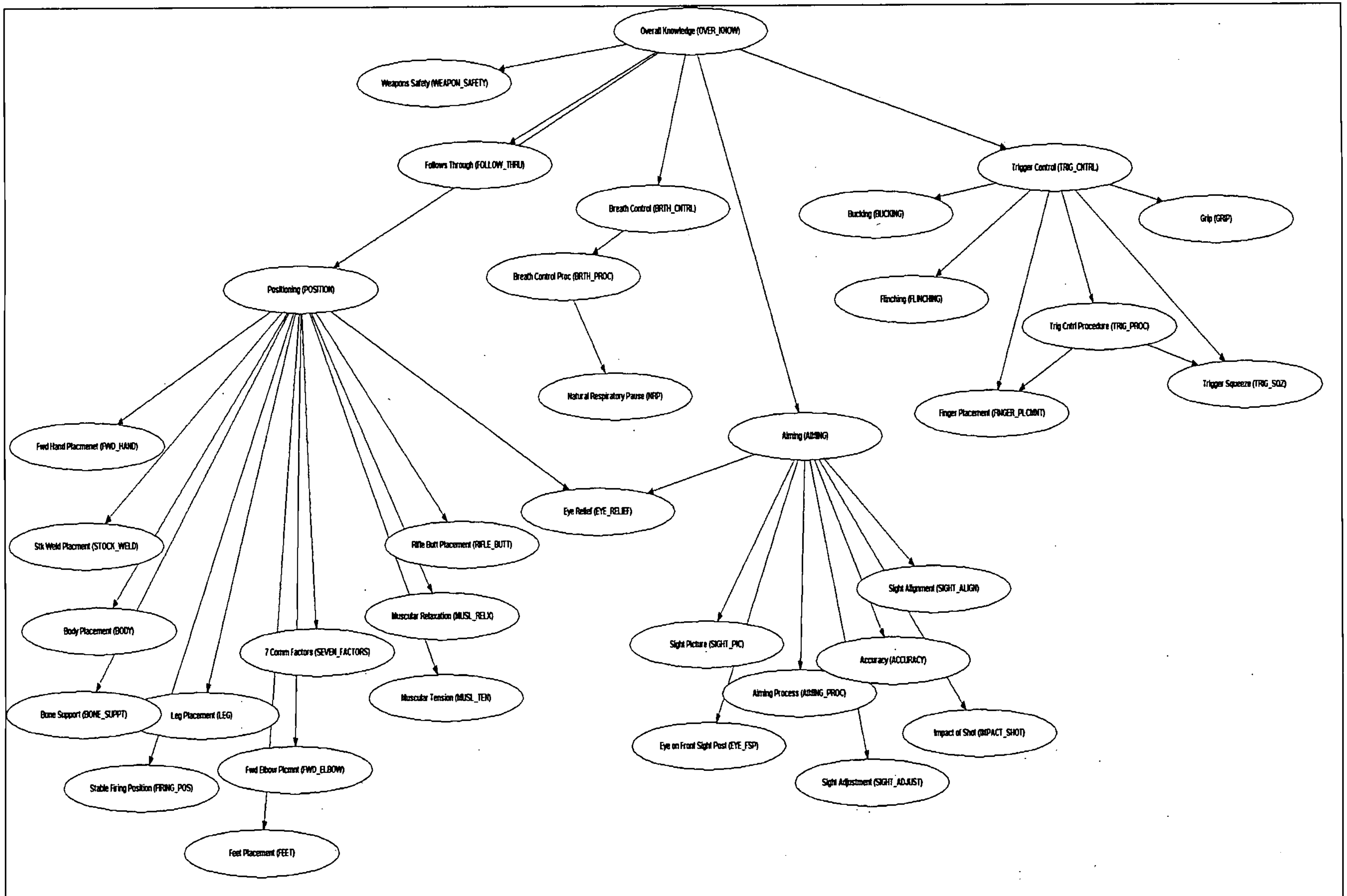

Figure 5. Bayesian network representing the knowledge dependencies for rifle marksmanship. Observable nodes are omitted for clarity and would in general be linked to the leaf nodes.

Conceptual indexing. Once knowledge gaps are identified, content needs to be retrieved and delivered to the Marine. The conceptual representation in the ontology plays one key role in this process—we use the domain experts' representation to guide the selection of relevant information. For example, suppose a Marine's knowledge of *TriggerControl* is identified as poor based on the probabilities yielded from the Bayesian network. Content from the topic *TriggerControl* is retrieved, as well as the neighbors of *TriggerControl* (i.e., fan-in and fan-out nodes). In this way the conceptual representation is used to retrieve presumably the most relevant and contextualized information.

The second key role is to use the performance on items of different cognitive demands to retrieve content at different grain sizes. Because the assessment items reflect different cognitive demands, presumably we have information on Marines' depth of understanding. Thus, we make use of the partitioning of content in each of the topics (see Figure 4) to deliver information at different grain sizes (e.g., definitions, explanations, elaborations, and so forth) depending on the Marine's performance on the different items.

To provide a concrete example of how such an approach would work, we present an example derived from a Marine's performance on assessments of rifle marksmanship. The example is for the concept of *TriggerControl* (the skillful manipulation of the trigger that causes the rifle to fire without disturbing sight alignment). A particular student scored poorly on items that asked for (a) a simple definition of trigger control, (b) how trigger control relates to sight alignment, and (c) the pattern of shots for a shooter with poor trigger control. From this set of observations, one inference that could be drawn is that this student has little or no knowledge of trigger control. The instructional remediation for this student could be to provide information on (a) trigger control—definition, explanation, and elaboration; (b) how trigger control is related to sight alignment (e.g., "A firm grip helps maintain good sight alignment because the grip helps ensure that the trigger is pulled straight toward the rear of the rifle."); and (c) the shot-dispersion pattern for poor trigger control with a picture and explanatory information.

Summary

We have described several uses of ontologies for assessment and instructional purposes. The technology behind ontologies has matured to the point that computational tools are readily available. In the context of rifle marksmanship, we described techniques for using ontologies for automated scoring of knowledge maps, conceptual searching, and individualized content delivery.

Example 2: Authoring Support for Assessment Design

Assessment Authoring Support

The promise of an ontology is in the presumably accurate (but not necessarily consensus) representation of the assessment model—the coherent packaging of concepts and links. This representation can be used for example, to provide guidance to assessment authors as they design assessments for particular purposes under particular constraints. If the ontology describes the conditions under which an essay task possessing particular characteristics is appropriate, then an assessment authoring system can, at minimum, check that authors of this particular essay task use the task to measure the appropriate type of knowledge.

An ontology that explicitly represents an assessment model implies a given structure and constraints (via the relations among concepts). For assessment authoring purposes, structure is of very high utility because it allows the enforcement of a common and consistent framework. This structure can be leveraged to assist assessment authors (particularly non-experts) in designing assessments. Assessment authoring support could be in the form of (a) aiding assessment authors to populate the assessment ontology with values specific to the users' purposes, and (b) system constraint checking that would ensure that assessment authors are alerted to incompatible values.

In terms of aiding assessment authors, an authoring system can traverse the assessment ontology and gather information from users for only those parameters that matter. This structure enforces the specification of important information and ignores variables outside the ontology. This scenario assumes the ontology is reasonably complete and accurate.

Constraint checking is carried out as the assessment author iteratively refines the values of the assessment parameters. An ontology network that converges to a steady-state condition implies that all constraints have been satisfied and all values for all assessment parameters are (simultaneously) acceptable.

Additional authoring support could be provided by folding in assessment guideline information. Because of the flexibility of the ontology structure, slots could be added to bind guideline information to specific assessment concepts. The purpose of providing assessment guideline information would be to bolster non-experts' (presumed) gaps in knowledge. Non-expert users are likely to have spotty knowledge of assessment in general—perhaps specific knowledge of only a few concepts and relations. Guidelines tied to concepts and relations should bolster what the assessment author knows about the domain, and just as important, what the person does not know. Similar applications of ontologies have been used to support physicians via clinical practice guidelines (Bernstam et al., 2000; de Clercq, Hasmon, Blom, & Korsten, 2001).

In a specific application of this approach, funded by the Interagency Educational Research Initiative (IERI), we are building an online, research-based system to assist middle school science teachers to build better assessments of complex learning. Because many educational assessments and accountability systems reflect neither rigorous subject matter analyses nor adequate attention to the cognitive demands of the tasks used, the validity and credibility of their results are suspect (Linn, Baker, & Dunbar, 1991). Our approach, model-based assessment, developed with OERI support (Baker, 1997; Niemi, 1996), offers a tested alternative. Tests and assessments intended to provide information to key users are based on common representations of states of student understanding, the cognitive demands of instructional and assessment tasks, and the structure of knowledge and procedures defining a domain within a subject area. From a common blueprint, assessments can be developed and summarized at different levels of granularity appropriate for instructional diagnosis or for summative purposes.

The Assessment Design and Delivery System (ADDS) we are building has three main features: (1) it provides utilities for individual teachers or teams of teachers to become designers and users of assessments that yield actionable information to guide their practice and student learning, (2) it embeds content, assessment, and pedagogical knowledge to assist teachers in both designing assessments and interpreting student progress, and (3) it produces valid results for classroom-based inferences with the potential for aggregation of results for policy uses.

Our work to date has focused on the knowledge construction and design work necessary to build the system. The first step was to construct an ontology of organizing concepts and principles in a key domain of middle school physical science, force and motion. To construct this ontology we elicited major concepts and principles from a team of six physicists over a two-day period. Figure 6 shows a map of some of these "big ideas" and the relationships among them. Beginning the construction of a domain is consistent with an extensive research base demonstrating that organization of knowledge typifies expert performance, and that domain knowledge, in the process of deepening understanding and developing greater expertise, becomes increasingly organized around abstractions such as concepts and principles (e.g., Bereiter & Scardamalia, 1986; Chi & Ceci, 1987; Chi, Glaser, & Rees, 1982; Glaser & Chi, 1988; Larkin, McDermott, Simon, & Simon, 1980; Niemi, 1996). Understanding of core principles and concepts results in more flexible and generalizable knowledge use, improves problem solving, and makes it easier to make sense of and master new facts and procedures (e.g., Ausubel, 1968; Chi & Ceci, 1987; Gelman & Lee Gattis, 1995; Larkin, McDermott, Simon, & Simon, 1980; Silver, 1981).

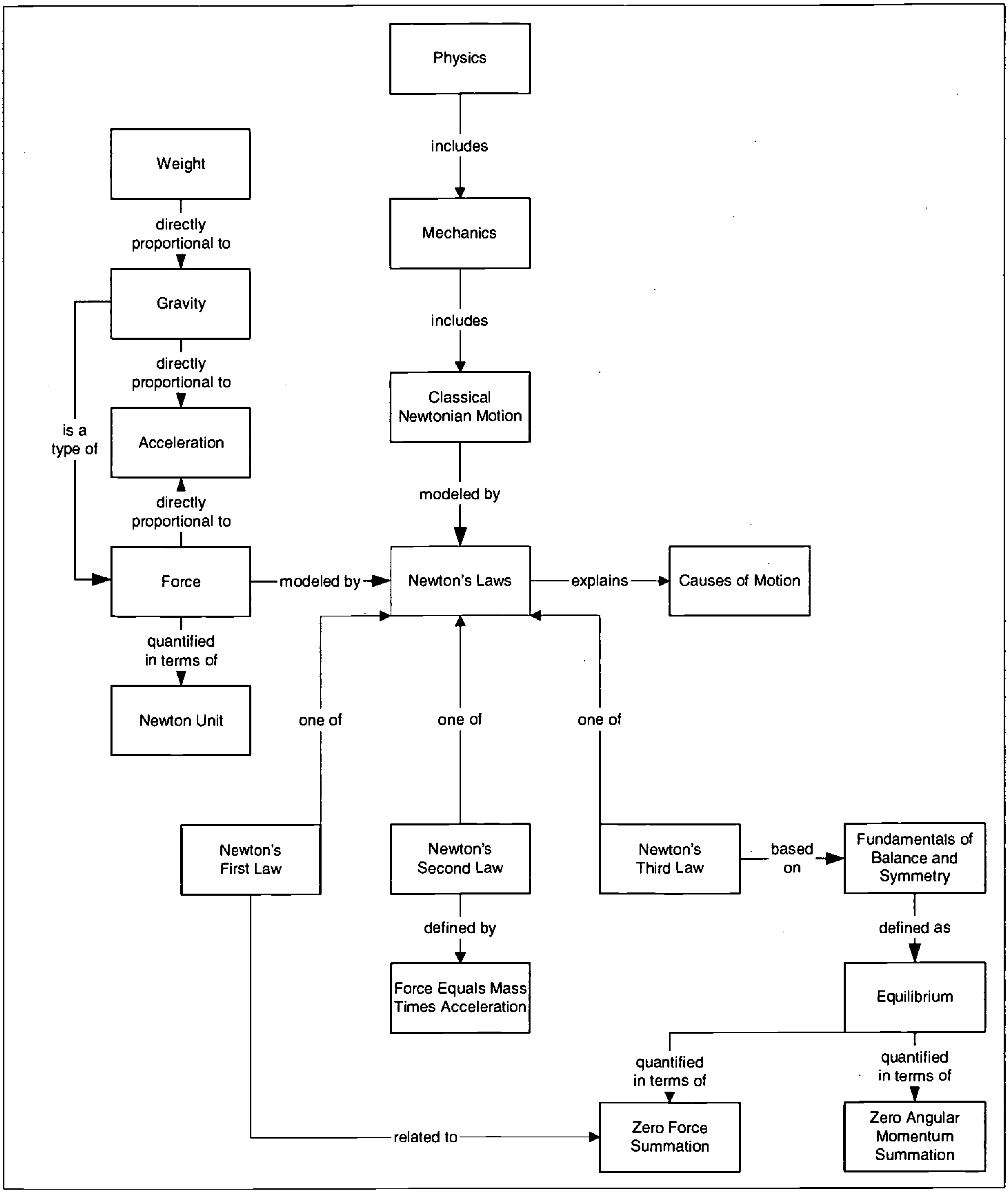

Figure 6. Part of an ontology for force and motion.

The second step in building ADDS was to identify the types of problems and tasks students should be able to complete in order to demonstrate mastery of each major element of knowledge in the ontology, and to identify the cognitive demands associated with each of those tasks. We have also developed an assessment database that holds both completed tasks and components of tasks such as information sources that may be textual, graphic, or multimedia. These information sources can be combined with other information sources and with questions or prompts to create new tasks. Tasks and task components in the assessment database are tagged with attributes that include: assessment purpose, type of assessment (explanation, problem solving, knowledge map), subject area and domain, relevant state standards, linguistic complexity, cognitive demands, development history, usage history, item quality, and scoring information. This tagging makes it possible to match tasks and components with elements in the domain ontology.

In essence ADDS matches standards or topics in physics to a domain ontology that has embedded within it links to an array of reusable assessment components. Teachers engaged in the assessment design process can start either with standards (analyzed in terms of cognitive demands) or with topics and types of knowledge in physics. ADDS will then guide them to select or build appropriate types of assessment. Appendix A shows the task builder screen that enables teachers to assemble task components, constrained by the standards or knowledge elements they are trying to assess. Ultimately ADDS will also contain a system for delivering and automatically scoring some assessments, and a reporting and interpretation tool to assist teachers in using the assessment information they obtain from the system. The reporting tool will use the Bayesian strategies sketched out earlier.

The use of ontologies to support assessment authoring seems particularly promising because of the nature of the anticipated authors: non-experts who lack breadth and depth of knowledge of assessment. An ontology-based authoring system can impose structure on the authoring task as well as check that user-specified values simultaneously satisfy all constraints among the assessment components.

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Appendix A

ADDS Task Builder Screen

Drag the elements that you would like to include in your task
(you can drag as many times as you want)

Information Sources

text | image | multimedia | complex

Questions / Prompt

?

Response:

explanation | short answer | knowledge map | multiple choice

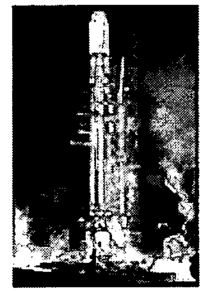
Scoring Information

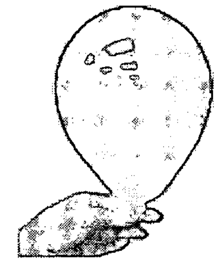
YES | NO

preview | save

Task Name

Sample rocket task





Consider the two systems shown above, a balloon and a rocket being launched in space.

a) Using what you know about physics and the applicable laws write an essay explaining and comparing the forces present in each system. In your essay be sure to discuss all the major similarities and differences between the two systems.

b) In which direction will the balloon travel once it is released? Explain your answer using what you know about forces. How is this similar to the rocket system? How is it different?

c) If you placed both of these systems in space, would you expect the movement of the rocket and the balloon to change compared to their movement through air? Would anything else change?

e) Explain why a rocket starts of moving slowly and gets faster and faster as it climbs into space. Does the same thing happen to the balloon? Why or why not?

Write your answer below:

Task information:
(the information below is important to correctly store the task you created)

Task type:
explanation ?

grade level:
6 7 8 9

subject area:
physics

domain:
Force and Motion

standard:
8.1.a

topic:
dynamics

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I. DOCUMENT IDENTIFICATION:

Title: Assessment Applications of Ontologies

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Corporate Source: UCLA

Publication Date: 4/2003

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