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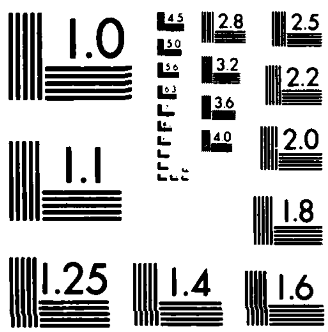
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A MULTIMEDIA KNOWLEDGE REPRESENTATION FOR AN "INTELLIGENT" COMPUTERIZED TUTOR

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The intended end product of our current research project is an "intelligent" multimedia tutoring system for procedural tasks, and in particular, for repair of physical objects. This paper presents the data structure that will be used. It is a graph with five types of nodes (mental, abstract, motoric or action, visual, and verbal) and two types of links (subconcept and pointer). The graph examples given in the paper are knowledge representations of conceptualizations that people might have for a simple object, a flashlight. We show how the representations are used for choosing actions, planning strategies, making inferences, and designing instructions. We give the plan for computer implementation of the tutoring system. We report previous applications of this knowledge representation, including how it can be derived from experimentally observed behavior. And we compare our knowledge representation to others.

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Abstract

The intended end product of our current research project is an "intelligent" multimedia tutoring system for procedural tasks, and in particular, for repair of physical objects. This paper presents the data structure that will be used. It is a graph with five types of nodes (mental, abstract, motoric or action, visual, and verbal) and two types of links (subconcept and pointer). The graph examples given in the paper are knowledge representations of conceptualizations that people might have for a simple object, a flashlight. We show how the representations are used for choosing actions, planning strategies, making inferences, and designing instructions. We give the plan for computer implementation of the tutoring system. We report previous applications of this knowledge representation, including how it can be derived from experimentally observed behavior. And we compare our knowledge representation to others.

I. Introduction

A. Research Overview

Our current research is focused on how to design interactive multimedia instructions for procedural, and more specifically, repair tasks. A repair is defined as follows: Suppose we have an object which has both structure and function. By repair we mean a modification of the structure, when the object has stopped functioning or is functioning incorrectly, in order to make it function properly again.

The main goal is to find the theoretical and practical principles for developing an "intelligent" computerized system for repair, while also actually developing such a system.

The method of the research, which we have just begun, is to build an experimental implementation using the data structures and procedures that act on them which are presented here and which come from our theoretical framework (Baggett & Ehrenfeucht, 1982, 1985). The system will be used in the domain of repair tasks. The main questions are:

1. Is our theoretical representation of knowledge (see below) an adequate description of the knowledge a person must have to perform repair tasks?

2. Can our multimedia knowledge representation be efficiently implemented as a tutor for repair tasks?

3. What types of tutor/user interactions can be used to communicate successfully the tutor's knowledge to the user? Theoretically, how can new information most effectively be entered into an existing representation?

4. What is the role of modalities of information (moving video, still photos, color graphics, verbalization) with respect to the concepts people form, and with respect to their being able to execute these concepts, i.e., perform the repairs?

5. (Related to 4.) What conceptualization does a person form as a result of the task? How does information from the tutor influence the person's conceptualization?

B. Purpose of this Article

The purpose of this paper is to present concrete examples of the multimedia knowledge representation which has not yet been implemented but which we plan to use as a data structure for the tutor. We take a relatively simple example, a flashlight. In III.A. below we show, in fairly complete detail, the knowledge representations for two different fictitious human conceptualizations of the flashlight, as viewed in our framework (Baggett & Ehrenfeucht, 1982). In III.B. we show how knowledge representations, as viewed in our framework, are formed and used for selecting actions, for strategies, and for making inferences. III.C. focuses on preparing individualized instructions for a repair task, and III.D. gives an overview of our plans to implement the ideas in an "intelligent" program which would be used as a teacher in a repair task.

II. Theoretical Background

A. The Theoretical Framework

The theoretical framework guiding this work, which has given rise to the explicit knowledge representation and processes acting on it presented below, concerns how people process information. It deals with concept formation and with encoding, retaining, and using information from multimedia stimuli. Within the framework a concept is represented as a graph with two kinds of associative links, and nodes corresponding to elements from different modalities, e.g., motoric (action), visual (pictorial), linguistic, and abstract. (Details are given in Baggett & Ehrenfeucht, 1982.) There is thus a single conceptual memory. (Many other researchers also assume a single conceptual memory, for example, Anderson & Bower, 1973; Carbonell & Collins, 1974; and Norman & Rumelhart, 1975.) The memory is connected to multiple processors. Processors can be thought of as processing visual input, auditory input, tactile input, and so on. Processors take input signals and put them into memory, forming concepts.

Concepts are not independent. If processor A builds a concept, then processor B can build another concept that is a part of it. This gives the hierarchical structure and the multimedia aspect: Visual, auditory, and motoric information, for example, can be part of the same concept. A theoretical approach similar to ours is that of Jackendorff (1983), who states that there is a single level of mental representation at which linguistic, sensory, and motor information are compatible.

We plan to analyze specific hypotheses arising in this new project within our framework, and, importantly, we expect that there will not be a situation in which we have to modify the framework (e.g., add a new link type) in order to do the analysis. The basic data structure does not seem to be too restrictive, and it appears that its efficiency is as good as any other proposed.

B. Selecting a Knowledge Representation

Work on knowledge representation in artificial intelligence has resulted in a variety of types of data structures for storing information in computer programs, and in procedures that manipulate the data structures in an "intelligent" way. We discuss here three criteria for evaluating a knowledge representation:

1. Can it be matched with the actual behavior of subjects? There are two sides here: (a) Can the representation be derived from behavior, and (b) Can it be used to predict behavior?

2. When the representation is used, does it contain the necessary and sufficient information for successfully performing the tasks it is designed to handle?

3. Is it efficient, i.e., sufficiently fast to be used on-line?

We briefly comment on the three criteria:

1. Matching the Representation and Behavior

(a) If the representation can be derived from behavior, it can be useful in designing individualized instructions, i.e., instructions that fit the way a particular person is conceptualizing a task. (We know from our own research, e.g., Baggett, 1983; Baggett & Ehrenfeucht, 1985, that such a conceptual match is important for performance. Lack of this ability in computerized instruction thus far is one shortcoming given by Sleeman and Brown, 1982. Its presence can be considered evidence that the program is indeed "intelligent".)

(b) The ability to use the representation to predict behavior gives the representation psychological validity.

We note that in a production system representation (e.g., Anderson, Kline, & Beasley, 1979; Davis, Buchanan, & Shortliffe, 1976; Davis & King, 1977; Hedrick, 1976; Lenat, 1982; Rychener, 1976; Shortliffe, 1976; Vere, 1977; Waterman, 1970), (a) is difficult and (b) is easy. In a semantic network representation (e.g., Anderson & Bower, 1973; Brachman, 1979; Carbonell, 1970; Carbonell & Collins, 1974; Hendrix, 1976; Norman & Rumelhart, 1975; Quillian, 1978; Stefik, 1980; Walker, 1976; Woods, 1975; Woods et al., 1976), (a) is easy and (b) is difficult.

2. Relativity of the Knowledge Representation

In evaluating what is a good knowledge representation, we keep in mind that there is no absolute or best or ideal one. (This fact was also discussed by Wilensky, 1984). Evaluation of the knowledge representation must be done relative to the task (i.e., the context or environment). There are two points here:

(a) The knowledge representation should not have extraneous elements, i.e., elements never used in a given group of tasks.

(b) The knowledge representation should be complete, i.e., within the group of tasks, all actions that can make a difference in the outcome must be accounted for (included).

3. Efficiency of the Representation

For a practically designed tutoring system, efficiency is an important issue. It can be divided into two components:

(a) Non-laboratory tasks, for which it is worthwhile to have a tutoring system, are fairly complex. So the size of the data base used for the knowledge representation can be a crucial element that determines the success or failure of the system.

(b) An interactive tutoring system requires real-time processing of data. Subjects should not have to wait long for its response (Anderson, 1984; Shneiderman, 1980). So the algorithms for data processing have to be fast.

In III. we propose a knowledge representation which seems to satisfy the three criteria above.

III. Representing Knowledge in the Theoretical Framework

A. The Representation

The 13 diagrams on pages A1 through A5 (Appendix 1) represent a fictitious (not experimentally derived) adult's conceptualization of a flashlight, as viewed in our framework. The seven diagrams on pages C1 through C3 (Appendix 2) represent a fictitious child's conceptualization, also viewed in our framework. Here is an explanation of the conventions used in the diagrams:

A ———→ B means B is a subconcept of A.

A - - - - - - - - -> B means A has a pointer to B.

Concepts in circles are abstract.

Concepts in triangles are motoric (actions). They are denoted by capital letters.

Concepts in squares are visual. They are executable by the visual processor. We label them V_i. The values for each V_i are given in Figure 1.

Concepts in ovals are linguistic. They contain verbal labels. In the diagrams, some subconcepts do not have linguistic components. This corresponds to the fact that many people do not have ready-made names for many parts.

Verbal explanations to the right of each diagram are <u>not</u> part of the concepts. They are merely explanations for the reader.

The division of the adult's conceptualization into 13 diagrams and the child's into 7 is done solely for the purpose of readability. Each conceptualization could just as well be one diagram.

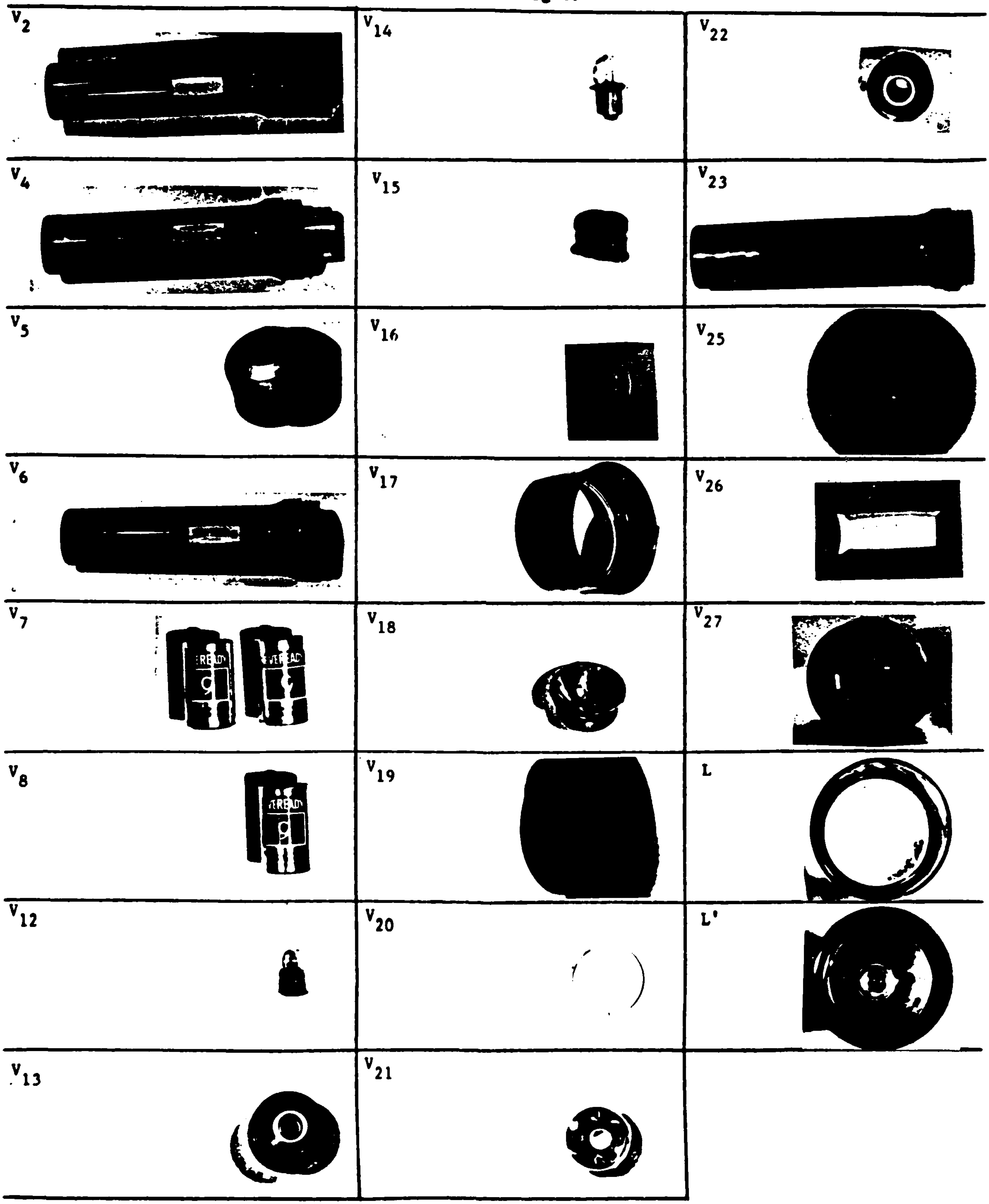
Now we shall discuss some properties of the diagrams in detail.

In diagram <u>2. structure</u> (adult), V_2 represents the flashlight as the person <u>sees</u> it. <u>(See Figure 1.)</u> A^{-1} has pointers to both V_4 and V_5. The <u>pointers</u> indicate that, if the person unscrews the cap, he or she <u>expects to see</u> a case with batteries (V_4) and a front part with protector and <u>bulb (V_5)</u>. <u>V_4</u> and V_5 are concepts executable by the visual system, so that the expectation can be verified. For example, if the actual flashlight whose cap was unscrewed did <u>not</u> contain batteries, execution of V_4 would fail to detect the batteries.

The pointer from A to V_2 indicates that if the person screws the cap V_5 onto the case with batteries V_4, the person expects to see a complete flashlight.

This pattern repeats in many diagrams. For example, for the adult, each action, besides having a verbal subconcept, also has one or more <u>visual</u> subconcept(s) which can be treated as arguments for the action. The <u>action</u> also has a <u>pointer</u> to one or more visually recognizable concepts, which represent the <u>objects</u> seen as the result of the action.

Figure 1. The values for visual concepts in the conceptualizations of the flashlight.



Other pointers from an action point to abstract concepts. An example is in diagram 2. structure (adult). Here, a pointer goes from action A to C_3, an electrical connection. This means that the action of screwing on the cap should cause the electrical connection between bulb and battery.

In diagram 3. functionality (adult), we see a pointer going from abstract concept 30 to L. This means the person expects the light to be off because the electric circuit is open. A pointer from abstract concept 29 to L indicates the light is one because the circuit is closed.

These examples show that the actual meaning of pointers (causal, expectations, etc.) depends on the types of concepts they are linking. In general, a meaning for the pointer will depend on the context in which it is used. In an example later in this paper, some pointers will indicate a temporal sequence of actions. Even in diagram 2. structure, pointers between A^{-1} and V_4 and V_5 could have a temporal interpretation: "First unscrew the cap, and then look at the case with batteries and the front part."

Similar ambiguities occur also in interpreting other parts of the diagrams. Concept A can be interpreted as a relation, i.e., "the front part is screwed on the case with batteries," as well as the action of screwing the front part on the case. Similarly, in 4. case with batteries, B can be interpreted as, "batteries are in the case," as well as the action of putting the batteries in the case.

This distinction of relation versus action that causes the relation is not represented in the concept. The distinction occurs only when the concept is used. For example, in assembling or disassembling a flashlight, the concepts would actually be executed, and then clearly they are actions. If the concept is used as a blueprint for a verbal description of the structure of a flashlight, the concepts A, A^{-1}, etc., are verbally represented as relations between parts of the object.

Turning now to a general overview of the adult and child conceptualizations, we can summarize their knowledge as follows. The adult has a fairly detailed knowledge of the structure, a reasonable knowledge of the circuitry, and some understanding of the relationship between the structure and the circuitry. The child has a much more limited knowledge of the structure and no knowledge about the circuitry. The child also has a restricted verbal terminology. We can also notice (in 6. case (child)) that the child does not view the contact bar as a part of the switch, but simply as a part of the body.

Another point needs to be mentioned here. Some things are left out of the conceptualizations presented. For example, there is no mention of the type of batteries or of electric current. Such omissions do not mean that the person does not have a knowledge of different types of batteries, etc. It only means that this knowledge is not incorporated as a subconcept of the concept of flashlight. (See also III.E.7 on world knowledge.)

B. Use of Concepts

1. Actions and Strategies

The concept of the flashlight as presented in the 13 diagrams allows our fictitious adult to perform many tasks, including repair tasks. For example, the sequence of actions $A^{-1} B^{-1}$ removes the batteries from the flashlight, and the sequence BA puts them back. This allows the person to change the batteries. Similarly, the person can change the bulb, or replace some other removable part of the flashlight.

The conceptualization presented above also allows the person to make some diagnoses of a malfunction. For example, if the light doesn't go on after the switch is pushed forward, the person knows something is wrong, because the expected result, as shown by a pointer from G to L (in 3. functionality) is that the light should be on. A pointer from 29 to L (in the same diagram) gives the information that the closed circuit causes the light to be on. Closer examination of a circuit (in the last adult diagram, p. A5) shows what connections have to be made, and which elements are part of the connections.

In addition, for example, the pointer in 5. front part with protector and bulb from C to C_2 indicates that snapping the protector into the back of the reflector should form connection C_2. This information could lead to the following actions: $A^{-1}C^{-1}CA$. These actions would remove the front part, remove the protector with bulb, snap it in again, and screw on the front part again. Such a sequence of actions could possibly correct a poor contact between the bulb and the collar.

For comparison, our fictitious child has far more limited possibilities for actions. When there is a malfunction, the child is basically limited to pushing the switch on and off, and replacing the batteries.

This brings up again the question of background knowledge: Can a person perform some actions based on general background knowledge? We think (we do not have experimental evidence) that background knowledge is used in the following way: Some specific concepts from background knowledge can be incorporated into the concepts that are processed. This means the person changes his conceptualization of the flashlight. Then the person bases his actions on his modified conceptualization.

But in order to perform even very simple specific tasks, the person needs a strategy. Without one, the actions available would not be performed, or would be performed in a random, aimless order. We think that application of a strategy consists of two parts:

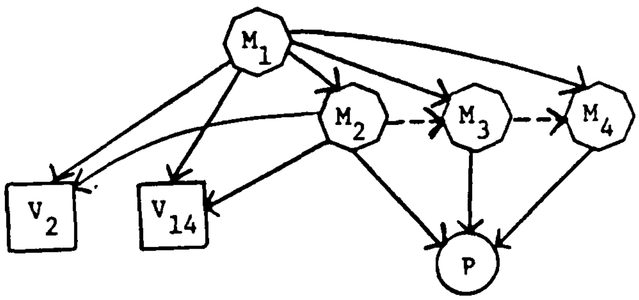
1.) Forming a plan of action, which basically consists of performing some mental operations; and

2.) Carrying out the plan.

Of course the two parts do not have to be done in the order given: A partial plan can be formed, and partial execution can be done.

In our framework, strategies are concepts, with an overall structure similar to the structure of an object such as the flashlight given above. The difference is that they will contain, among other elements, executable mental actions. Executable mental actions are treated in the same way as executable motoric actions, with one difference. Motoric actions, when executed, operate on physical objects. Mental ations, when executed, operate on concepts.

In the examples below, we shall indicate executable mental actions by putting them in octagons: (M). We shall start with an example of a strategy for removing the bulb from the flashlight (Figure 2), and later generalize it to removing a part (subassembly) from an object.



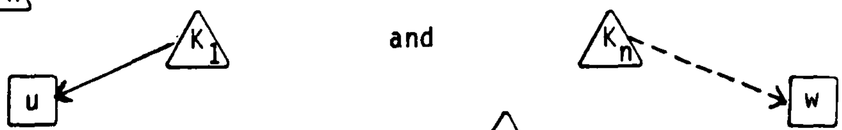
M_1. concept of removing bulb from flashlight
M_2. Form a plan.
M_3. Carry out the plan.
M_4. Forget the plan.
P. Abstract plan (there is nothing in it)

Figure 2

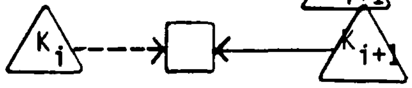
Mental operations can be <u>defined</u> in terms of subconcepts, the subconcept relation, and pointers. Below, we give the definitions of M_2, M_3, and M_4.

<u>Definitions.</u>

(Preliminary definition) A <u>chain</u> between [u] and [w] is a sequence K_1, ..., K_n of concepts <u>such</u> that



and each K_i points to a subconcept of K_{i+1}, i.e.,



Here is an example taken from our adult's conceptualization.

A^{-1}, C^{-1}, D^{-1} is a chain between [V_2] and [V_{14}]. The reason it is a chain is shown in Figure 3.

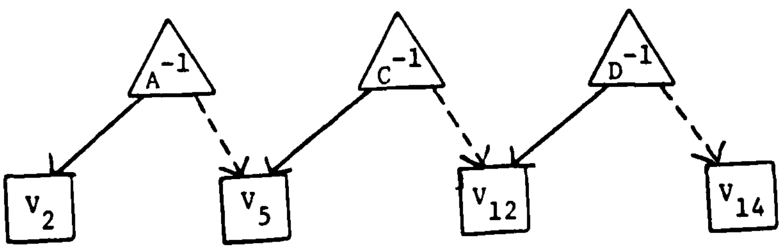


Figure 3

Definition of M_2. M_2 consists of 2 steps.

Step 1. Find a chain from V_2 to V_{14}.
Step 2. Make all elements of the chain subconcepts of P.

(On paper, it is shown as follows: Solid arrows are drawn from concept P to elements of the chain. See Figure 4.)

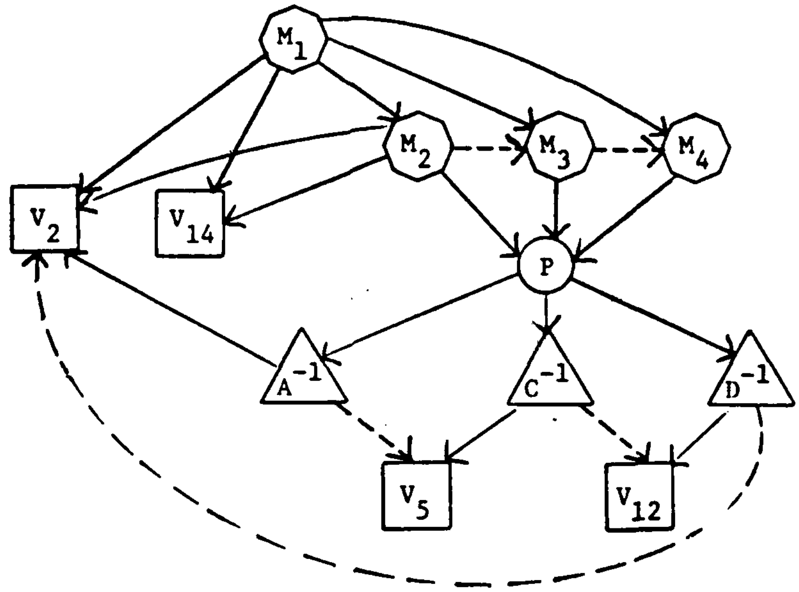


Figure 4

Definition of M_3. Execute all subconcepts and subsub....concepts of P in order, constrained as follows:

(a) A subconcept must be executed before its concept; and

(b) If one concept points to another, the second one must be executed after the first.

Definition of M_4. Remove all subconcepts of P. (On paper, it is shown as follows: Erase all solid arrows that start in P.)

The concept M_1 is a strategy specific for the flashlight. This can be seen by observing that subconcepts V_2 and V_{14} are common subsubconcepts for M_1 and for 1 (on p. A1), the adult's concept of flashlight.

(1) execution of M_2 (mental, which would lead to modification of P (making P concrete). This gives the concept shown in Figure 4.

(2) execution of M_3, which consists of the following sequence of physical actions:

1. V_2 Look at (locate) flashlight.

2. A^{-1} Unscrew cap.

3. $\boxed{V_5}$ Look at front part.

4. $\triangle C^{-1}$ Tilt and remove protector from back of reflector.

5. $\boxed{V_{12}}$ Look at protector with bulb.

6. $\triangle D^{-1}$ Take bulb out of protector.

7. $\boxed{V_{14}}$ Look at bulb.

(3) execution of M_4 (mental, which restores the original abstract P (shown in Figure 2 above.))

We observe three things:

(1) The execution of M_2 makes the plan P concrete (in terms of Baggett & Ehrenfeucht, 1982).

(2) In the execution of M_3 (carrying out the plan), motoric components direct the actions, and visual components direct the attention of the person performing the action.

(3) *Execution of* M_4 *is an* example of an abstraction. It removes all subconcepts from P, returning it to its original abstract status.

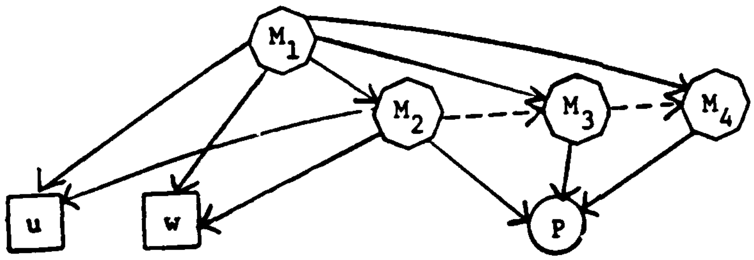
We shall now show how strategies for removing other parts of the flashlight can be obtained from the strategy shown above, by transfer of learning.

In order to remove the batteries of the flashlight, one needs only to replace V_{14} by V_7 in Figure 2. The reader may check that the execution of such a modified concept would indeed remove the batteries. Similarly, replacing V_{14} by V_{20} would lead to removing the transparent disc.

We note that replacement of V_{14} by V_{22} would lead to a concept that would fail to execute, because there is no chain between V_2 and V_{22} in the concept of the flashlight. (The collar is nondetachable.) But of course the metal part, which the collar is a part of, is detachable and can be removed from the flashlight by replacing V_{14} by V_{18}.

We note also the role of M_4. We assume for a moment that M_4 is not present. (This would be the situation depicted in Figure 2, but with no M_4.) This strategy would lead to the correct removal of the bulb from the flashlight. But attempting the first editing operation, namely, replacing V_{14} by V_7, would give a different result than before. Namely, execution of M_2 would simply add new subconcepts to P, which already has subconcepts assigned, from previous use. It would lead to a sequence of actions which would remove the batteries and remove the bulb. This is an example of carrying unnecessary actions from a previous task to a new task during transfer of learning. The error is rather typical, and in this case it is solely due to not performing the abstraction operation (that is, to not removing elements from the plan P from the previous task).

A general strategy for removing a part of an object is as follows. We take again our original Figure 2 and make V_2 and V_{14} undefined, as shown in Figure 5.



M_1. concept of removing a part from an object
M_2. Form a plan.
M_3. Carry out the plan.
M_4. Forget the plan
P. Abstract plan

u and w are undefined

Figure 5

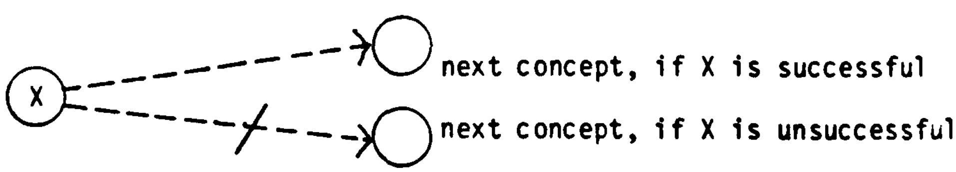
That u and w are undefined means that the type of u and w is still a visually executable concept, but they are not executable. That is, they do not have a value that actually corresponds to a visual image.

Obtaining Figure 5 from Figure 2 is an example of generalization, as given in Baggett & Ehrenfeucht, 1982.

We observe that the concept in Figure 5 is not flashlight-specific. (It does not have any subconcepts in common with the flashlight concept.) It can be applied to the conceptualization of any object.

This concept of removing a part is still unsatisfactory in some respects. In particular, the strategy it represents does not tell what to do if execution fails, for example, if a plan is not found, or if execution of the plan fails, for one reason or another.

For an executable concept X we will denote by X' the failure of execution. (This convention can be seen in 3. functionality (adult), where L' denotes failure to detect the light.) When there are pointers going out from an executable concept, we will make a distinction about which pointers have to be followed when the execution is a success versus when the execution is a failure. We graphically represent this as follows:



(We are not introducing an new type of pointer. We are simply indicating which pointer has to be followed, depending on the success or failure in the execution of concept X.) We note that this is the simplest (and most important) example of automatic decision making, as viewed in our framework.

In the example in Figure 6, we have added new linguistic subconcepts to our concept of removing parts. (Linguistic concepts are executable in our framework.) So now, application of the strategy in Figure 6 to any object would lead to one of three outcomes:

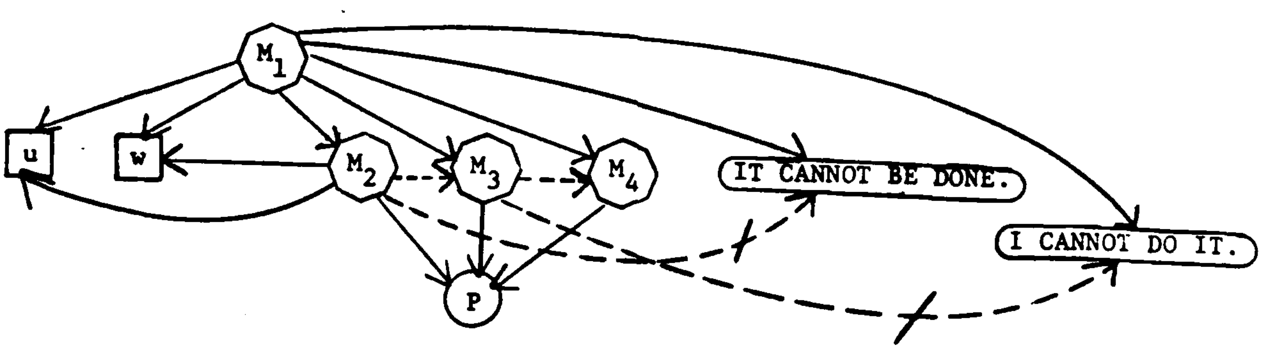


Figure 6

(1) removing a part, or

(2) verbal output, "it cannot be done," for the case where a plan cannot be formed; or

(3) verbal output, "I cannot do it," for the case where the plan was successfully formed, but execution of the plan failed, that is, one of the motoric or visual components of the concrete concept P failed to execute.

2. Inferences

Our framework does not include any system of formal rules of logic. There are two reasons for this. First, we doubt the psychological validity of logical rules, as formulated in logical systems (people don't seem to think according to the rules of logic). Second, we don't see the need for such a set of rules in our framework.

Basic inferences are directly represented by pointers in our knowledge representation. There is one difference between our approach and logical inferences: In our representation, a pointer from G (push switch forward) to L (light is on), shown in 3. functionality (adult), does not indicate that whenever the person pushes the switch forward, the light will be one. It indicates only that after pushing the switch forward, the person should expect the light to be on, and should try to confirm the expectation in this case by looking for the light.

Forming a chain of reasoning is not obtained by application of any rules of logic, but by the search for a chain of concepts, as in the example above. The definition of chain given above is just an example. Different definitions of chains would correspond to different methods of reasoning.

Another example of inference is given in Figure 6, when the person says, "It cannot be done." In this case, the inference is very simple. "It cannot be done" expresses the fact that the plan for action cannot be formed, and therefore action is impossible. This shows, among other things, that all inferences are not universal (in our framework). Rather, they are situation-dependent. The conclusion, "It cannot be done," would be reached by our fictitious child, when the child is asked to remove the bulb from the flashlight. But it would not be reached by our adult.

C. Instructions

Let us assume that the adult above wants to teach the child how to fix a malfunctioning flashlight, or to do some other task related to the flashlight. (For convenience we henceforth refer to the adult as A and the child as B.) We consider that there are two essential elements in this process:

(1) A needs to find out what B knows. This means A should construct a concept that is as close as possible to the concept B has. Ideally, A will have, besides his own concept of the flashlight, also the concept of the flashlight that B has.

(2) A has to instruct B. The method of instruction within our framework will be just a strategy, requiring planning and actions. A can use different strategies, depending on the situation, but all will have one thing in common: The objective of the instruction is to make B modify his concept in some specific way. (In our framework, this means that B has learned.)

There are many possibilities for A to achieve (1) mentioned above. One is to give B some task to do involving the flashlight and see how B performs.

In our example, suppose A gives B a flashlight with a burned out bulb and says, "Can you fix it for me?" Here are some hypothetical reactions of B, based on B's conceptualization: B pushes the switch forward and backward a few times with no result. He then says, "The batteries are bad. Do you have any good batteries?" After being given new batteries, B replaces the old batteries with the new ones and pushes the switch several more times, again with no results. He says, "I cannot fix it. It is broken."

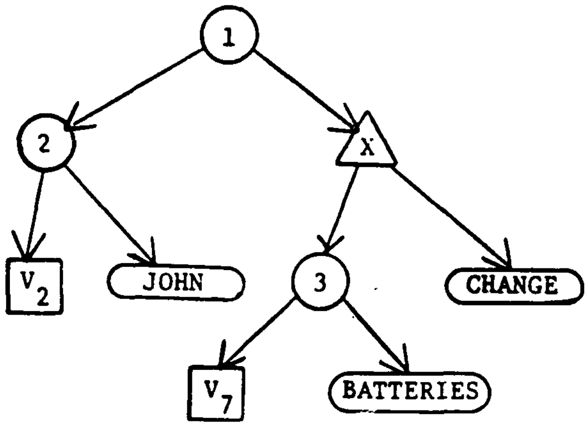
We notice this simple interaction gives a pretty fair summary of B's conceptualization, both in terms of the actions that B can perform, and his knowledge about how the flashlight works.

But A's interpretation of B's behavior depends on A's conceptualization of a flashlight. In order to obtain B's conceptualization, A needs: (A) his own conceptualization and (2) an observation of B's behavior. This brings up a new mechanism not mentioned in the above example. The mechanism is building new concepts (in this case, the conceptualization of B), based on the concepts that A already has and on input stimuli, an observation of the behavior of B. Treatment of this problem will be discussed in part III.D.4 of this addendum.

Regarding (2) above, the method of teaching is treated as any other strategy: it involves planning and execution of the plan.

We discuss here a small but important technical point: How, in our representation of knowledge, will actions performed by different people be represented?

Suppose John changed the batteries. This information would be represented as in Figure 7.

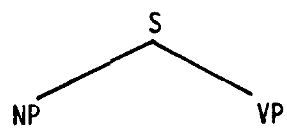


1. John changed batteries, or Batteries were changed by John.
2. the person John
3. batteries
X. action of changing

Figure 7

This representation differs from the representation used in semantic networks, where John and the action would be directly connected by a labelled pointer, indicating that John is the actor of the action. it also differs from the propositional approach, in which John would be treated as an argument of the action in the proposition.

Our approach, on the other hand, is the one used in standard linguistic processing, where simple sentences are divided into noun phrase and verb phrase:



NP corresponds to John, and VP corresponds to an action, together with its arguments.

Thus, our person A would represent the fact that B replaced the batteries as in Figure 7 (with B substituted for John).

D. An Overview of the Proposed Programs

The (planned) program will consist of:

(1) a data base
(2) special purpose procedures

    (a) concept processing procedures
    (b) output procedures

(3) an English parser
(4) a concept building procedure
(5) a driver

Each of these will be briefly discussed.

(1) The data base

The data base will contain knowledge represented as concepts, as shown above. It will contain a concept of the object, with the amount of detail corresponding to the amount of detail used in the description of person A above. It will also contain repair concepts that would correspond to the concept of removing a part of the object, as shown above.

We have estimated that a detailed representation of a concept for repairing the flashlight, one that would cover a malfunction in any part of the electric circuit or in a mechanical part, or in a combination, is approximately of the same size as the description of the flashlight given for the adult. (We use here the number of subconcepts as a measure of the size.)

The data base will also contain a teaching strategy. Its size will depend on the strategy used. Also, other concepts will be built by the program and added to the data base during interaction of the program with the subject.

The concepts which will be put in the data base (conceptualizations of the objects, repair strategies, etc.) will be experimentally derived and tested (and not fictitious, namely, invented by the experimenter, as were the concept of the flashlight given above).

(2) Special purpose procedures

(a) concept processing procedures

The program will contain basic procedures corresponding to basic mental operations such as M_2, M_3, and M_4 above. (A special procedure for M_1 is not needed, because execution of M_1 consists of execution of M_2, M_3, and M_4.) Among the basic procedures, there will be ones for concept comparison, which have not been illustrated in the examples above. (All special purpose procedures will be data-driven. That is, the order in which they are evoked will be determined by concepts in the data base.)

(b) output procedures

The program will also contain procedures that control visual and verbal displays on the screen. These will also be data-driven, in the following way: Each motorically executable concept (as in the examples above) will correspond to having one the screen a segment of videotape showing performance of the action. Visual concepts will correspond to still pictures. Linguistic concepts will provide the text. Thus, the action of the program in executing concept M_1 (in figure 4), stored in the data base, will be as follows:

(1) Execution of M_2: Search through data base, constructing a chain, and connect the chain to P.

(2) Execution of M_3: Show on the screen the sequence

(i) still picture of flashlight
(ii) moving video of unscrewing cap
(iii) still picture of front part

(iv) moving video of tilting and removing protector from back of reflector
(v) still picture of protector with bulb
(vi) moving video of taking bulb out of protector
(vii) still picture of bulb

We note that this part of the program is the most task-specific. Clearly, the visual display will depend on the object to be repaired.

(3) English parser

The English parser will take the subject's input and construct a very simple knowledge representation of it (in the form of a concept), as is shown, for example, in Figure 7.

At the present time some students of A. Ehrenfeucht in the Computer Science Department are testing a rather sophisticated English parser, written in LISP, that possibly can be used for this purpose.

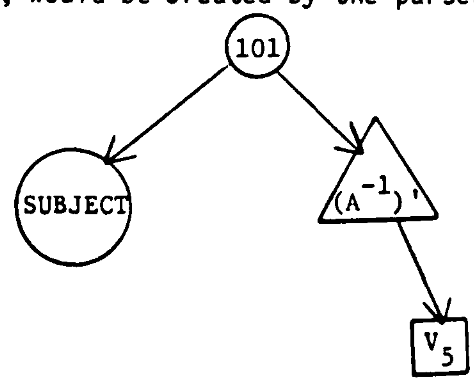
(4) Concept building procedure

This procedure is the most complex part of the whole program. It will take as its input the sequence of interactions between a subject and the program, and the concept of the object from the data base, and return to the data base a new concept, "how, at a particular point in time, the subject conceptualizes the object," Similarly, when taking from the data base the concept of "how to repair the object", it would return the concept, "how the subject thinks the object should be repaired."

To be a little more specific, let us assume (still using the flashlight example) that the following sequence has been shown on the screen:

still picture of flashlight
moving video of unscrewing cap
moving video of removing batteries
moving video of putting batteries back in
moving video of screwing cap back on

The subject's response, typed on the terminal, is, "I cannot unscrew it." From the point of view of internal processing, the special purpose output procedures A^{-1} B^{-1} BA were evoked. The concept, call it 101, shown in Figure 8, would be created by the parser.



101. Subject cannot unscrew the cap.

$(A^{-1})'$ action of unscrewing the cap was unsuccessful

Figure 8

The sequence A^{-1}, B^{-1}, B, A, 101 is the actual input for the concept building procedure. After this interaction, the concept of how the subject conceptualizes the flashlight would have A^{-1} as a nonexecutable subconcept.

The algorithm used in the concept building program will be a modification of the cluster analysis algorithm described in Perry (1983).

(5) A driver

A driver will synchronize the action of other procedures and keep track of concepts in the data base which are processed at a given time.

E. Comparison of the Proposed Knowledge Representation with Others

The knowledge representation we proposed seems to satisfy the criteria in II.B., 1, 2, and 3, above. Further, each of the three elements has been partially tested in practice. Some of the details (e.g., for matching behavior in a repair task with the representation) were presented in Baggett (1984). We give here a brief summary.

1.a. We can construct a subject's hypothetical conceptualization from the subject's performance (Baggett, 1983, 1984; Baggett & Ehrenfeucht, 1985. Baggett & Perrig, 1985).

1.b. We have been able to manipulate subjects' assembly performance by changing the representation of an object presented in an instructional videotape. (These were the "typical" vs. "minority" conceptualization results presented in Baggett & Ehrenfeucht, 1985). This means that our representational approach is psychologically valid and predictive.

2. Regarding relativity of the representation, when we match performance of a subject to the representation, we know what is never used and what is needed to make a complete representation. Further, we know how to test for extraneous material and completeness (Baggett, 1984).

3. Concerning the efficiency of the representation, we know about the size of the data base from objects containing nearly 100 pieces and over 100 physical connections. We also know about the algorithms which will operate on the data base.

First, in our assembly tasks we have worked with conceptualizations (representations) from hundreds of subjects. The data bases constructed were fairly small. Preliminary results from our repair tasks show that the data bases will be of similar size. Second, the algorithms we have used (Perry, 1983) have been fast enough for the tasks we have analyzed thus far. They have not been tested, however, in real-time use, that is, for processing that must be done while the subject works at the terminal.

4. A Comparison of Our Representation with KRL

Henry Halff (personal communication, 1983) asked whether KRL, a knowledge representation language (Bobrow & Winograd, 1977), has similarities with our representation. We very briefly discuss the similarities and also the differences.

a. In KRL knowledge is organized around conceptual entities. This is similar in our approach in which conceptual entities are primitives. However, KRL stresses descriptions associated with the entities, which we do not have.

b. Partial knowledge is represented in both approaches. We have different decompositions (conceptualizations); KRL has different descriptors. KRL represents different viewpoints; we have different representations for different purposes.

c. Both approaches are object-oriented. But our approach treats reasoning as an object, the same as other concepts. For us, a strategy, or the logic used, *etc.*, are objects just as any other concepts are.

d. KRL clusters its information according to its use by processors. We do not. For us, a concept contains a mixture of elements, to be used by various processors.

e. KRL is a language. We are not trying to develop a language for our knowledge representation. We can use any number of existing languages.

The most important difference between KRL and our approach is that KRL works with text objects and descriptions, while in our data base visual elements are an essential part. Some objects in our data base do not even have a verbal description, except for a simple label for identification. For example, in our sequencing of the shots of a videotape (Baggett, 1984), there are no linguistic descriptions of what the sequences show, and such descriptions are also not needed.

5. Our Approach and Frames and Semantic Networks

Conceptually, our approach is closer to frames (Minsky, 1975; Bobrow & Winograd, 1977; Goldstein & Roberts, 1977; Novak, 1977; Charniak, 1978) than to any other class of representation.

Mathematically, it is closer to semantic networks, but our nodes and links mean very different things (see III. above) than they do for semantic networks.

One difference with semantic networks is that our procedures (e.g., strategies, etc.) are objects of the same status as any other data; they are concepts that are executable. When procedures are used, they are executed (mentally or physically).

6. Our Approach Contrasted with Paivio and Linguistically Based Theories

The main difference between our knowledge representation and that of Paivio (1971) and others is that in our representation each concept contains a mixture of elements of different types: abstract, motoric, visual, and verbal. (As mentioned in II.A., Jackendorff (1983) hypothesizes a level of representation at which linguistic, sensory, and motor information are compatible. He does not specify the structure or processes in detail, however.) Paivio's approach specifically postulates a distinction between verbal and imaginal processing (dual code). He treats both processes as parallel and as operating on different objects.

Some other approaches (for example, Kintsch & van Dijk (1978) and some versions of semantic networks) concentrate almost exclusively on processing linguistic elements, and put everything else in the category of "world knowledge."

7. The Role of Background, or World Knowledge

Our approach differs from others on the role of background or world knowledge in problem solving, that is, in doing a specific task. In our framework (as was briefly mentioned in III.A. above) the role of background seems to be very unimportant. Namely, either elements needed to solve the task are already incorporated into the concept involved in solving the task (just as some knowledge of the circuitry is incorporated into our adult's conceptualization of a flashlight), in which case the concepts used are sufficient by themselves to solve the problem (or perform the task); or necessary elements are not incorporated, in which case an attempt to perform the task would fail until the concepts are modified and extended.

IV. Final Remarks

In the introduction to their 1982 book Intelligent Tutoring Systems (ITS), Sleeman and Brown state that the designers of intelligent tutoring systems, such as Brown, Burton, and deKleer (1981), Burton and Brown (1981), Clancey (1981), Genesereth (1981), Goldstein (1981), Kimball (1981), Miller (1981), Sleeman and Hendley (1981), and Smith, Graves, Blaine, and Marinov (1975), are dissatisfied with their system's overall performance. They continue, "The following are some of the acknowledged shortcomings:

(1) The instructional material produced in response to a student's query or mistake is often at the wrong level of detail, as the system assumes too much or too little student knowledge.

(2) The system assumes a particular conceptualization of the domain, thereby coercing a student's performance into its own conceptual framework. None of these systems can discover, and work within, the student's own (idiosyncratic) conceptualization to diagnose his "mind bugs" within that framework.

(3) The tutoring and critiquing strategies used by these systems are excessively ad hoc reflecting unprincipled intuitions about how to control their behavior. Discovering consistent principles would be facilitated by constructing better theories of learning and mislearning--a task requiring detailed psychological theories of knowledge representation and belief revision.

(4) User interaction is still too restrictive, limiting the student's expressiveness and thereby limiting the ability of the tutor's diagnostic mechanisms." (p. 3)

Our approach contains methods for potentially reducing, and perhaps eliminating, these shortcomings. Very briefly, we consider each of the 4 points above and how our system will treat it.

1. Information at the wrong level of detail. (ITS)

Our system (program) will discover what a subject's conceptualization is, namely, what the subject knows. Using a concept comparison procedure, it will compare that conceptualization to what the conceptualization should be. Therefore it can be very much on target in providing the information the subject needs to know to properly modify his concept. (It can be far more accurate than device model instruction (Kieras and Bovair, 1983) as well; device model instruction provides the same information for everybody.) The system can also test if the information provided is incorporated into the subject's conceptualization.

2. The system coerces a student into its own conceptual framework. (ITS)

Our approach can potentially make a large contribution here. Our system (program) will derive an individual subject's own conceptualization, and communicate with the subject using his own conceptualization.

3. Strategies are based on unprincipled intuitions. Better theories of learning need to be constructed. (ITS)

We have (in our theoretical paper, parts I and II) the beginnings of a detailed theory of learning. This research will be an opportunity to give it a major test.

4. User interaction limits a student's expressiveness, thereby limiting the tutor's diagnostic ability. (ITS)

First we consider subject-to-program communication. In our past work we have found that we can construct a subject's conceptualization of the structure of an object he is building, from an abstract graph and order of request for pieces. Such information can be obtained without any verbal input from the subject. This approach will be included in the design of the concept building procedure in our program. It will rely very little on the linguistic content of a subject's response, but mainly on the order of responses and possibly the time between responses. Therefore, construction of the subject's "conceptualization," which is needed for a diagnostic of the subject's problem, will not be severely restricted by limitations of the parser.

Second, we consider program-to-subject communication. In our present work we have found that a properly organized visual presentation plays a major role in instructions for how to build an object. The accompanying linguistic information clearly plays a far smaller role. The planned program is heavily biased toward presenting pictorial output. (Of course, the actual ratio of verbal to nonverbal material will be determined experimentally.)

A significant difference between the program presented here and some other "successful" programs (for example, MYCIN (Shortliffe, 1974, 1976) and GUIDON (Clancey, 1981) is as follows. In MYCIN and GUIDON, for example, there is a clear division between the expert part and the teaching part. Here, we do not have that distinction at all. All elements (student modeling, factual knowledge, inferences and teaching method) are treated uniformly.

We hope that the theoretical ideas given here, and their practical implementation, may contribute to reducing or eliminating the main shortcomings of current programs that have been acknowledged by authors of intelligent tutoring systems.

Researchers working in cognitive architectures and their relationship to behavior (e.g., Anderson, 1984; Bobrow & Winograd, 1977; Langley, 1984) have observed that for an intelligent tutoring system, choosing a good representation for a set of tasks is crucial. A key point that we emphasize is that our knowledge representation seems to be right for the set of tasks that we plan to study. For example, we have had success in partially testing it. The representation is simple but powerful and seems to contain the right components. We discussed above how it can be matched with subjects' behavior, that it is complete and does not contain extraneous elements, and it seems to be efficient. Further, its multimedia aspect seems to be (other than the work by Munro and his colleagues on the General Maintenance Training Simulator) unique.

Anderson (1984) has urged that computerized tutors be used by many researchers as a paradigm for studying and testing theories of learning and skill acquisition. We hope to contribute to this effort, and we expect that through the research proposed here, our theoretical framework will develop into a full testable theory.

Footnote

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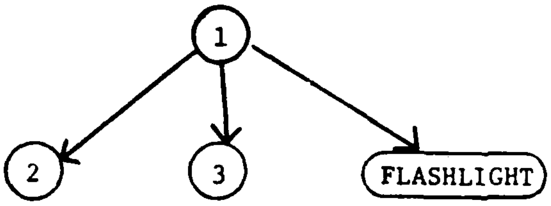
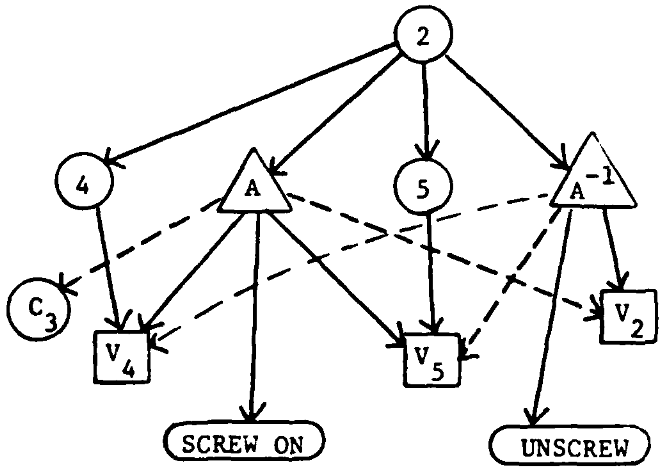
The 13 diagrams below (on pages A1 through A5) represent a fictitious adult's conceptualization of a flashlight.



1. flashlight
2. structure
3. functionality



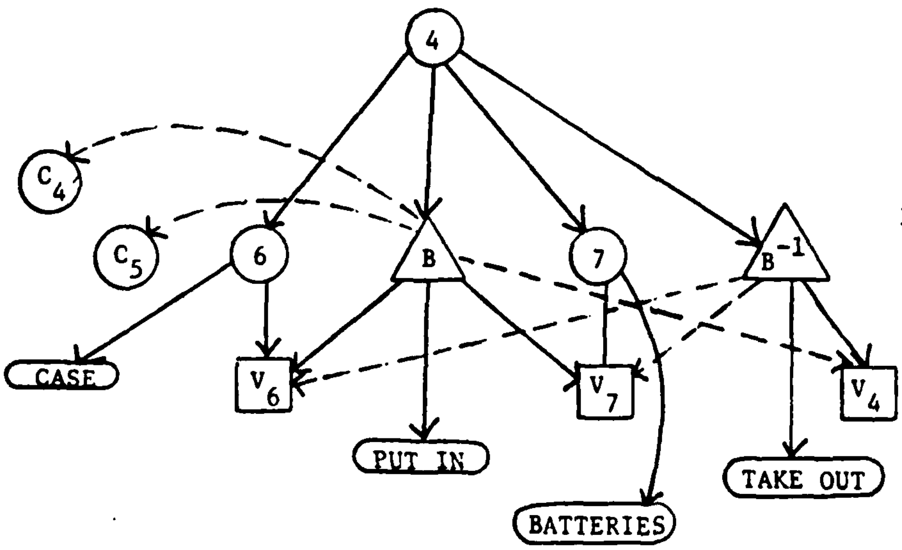
<u>2. structure</u>

4. case with batteries
5. front part with protector and bulb

A. screwing on cap

A^{-1}. unscrewing cap

C_3. electrical connection; see <u>29.</u> and <u>30.</u> below.



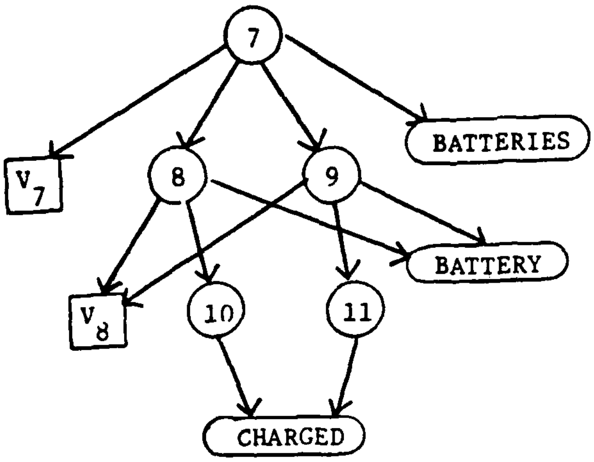
<u>4. case with batteries</u>

6. case
7. batteries

B. putting batteries in

B^{-1}. taking batteries out

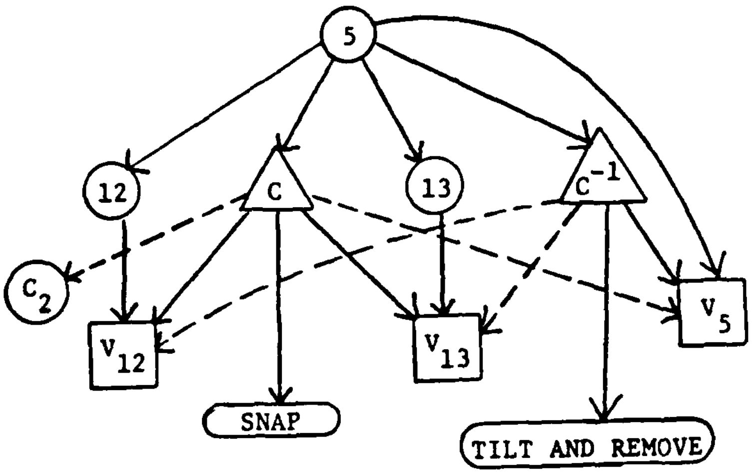
C_4 and C_5. electrical connections; <u>29.</u> and <u>30.</u> below.



7. batteries

8. one battery
9. another battery
10 and 11. each battery is charged

$V_9 = V_8$ because the batteries are visually identical.



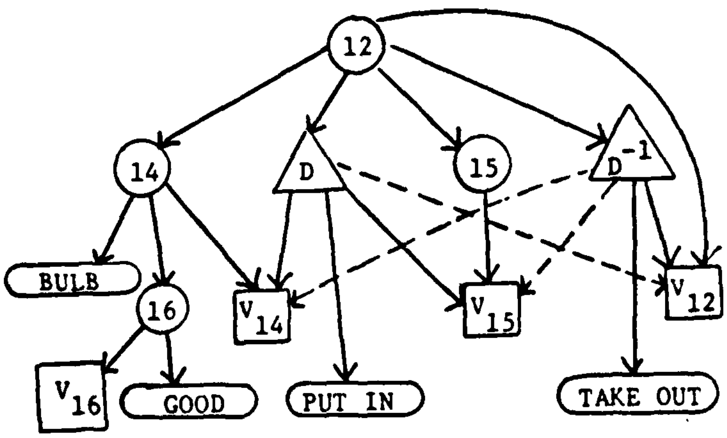
5. front part with protector and bulb

12. protector with bulb
13. cap

C. snap protector into back of reflector

C^{-1}. tilt and remove protector with bulb from back of reflector.

C_2. electrical connection; see 29. and 30. below.



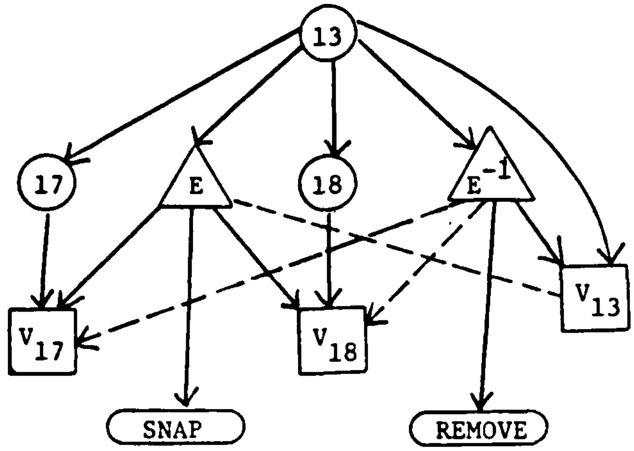
12. protector with bulb

14. bulb
15. protector
16. not burned out

V_{16}. continuous filament can be seen in bulb

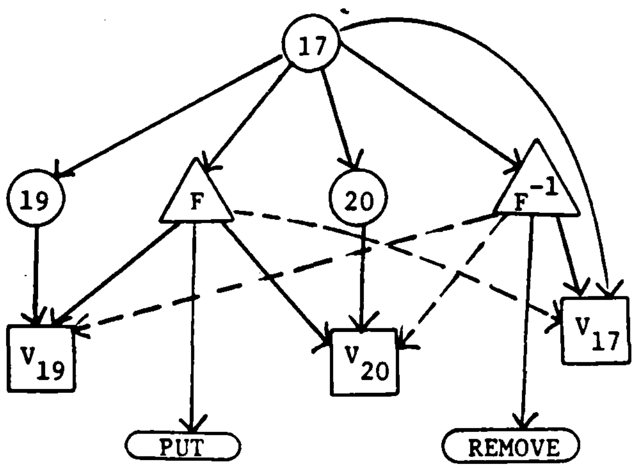
D. put bulb into protector

D^{-1}. take bulb out of protector



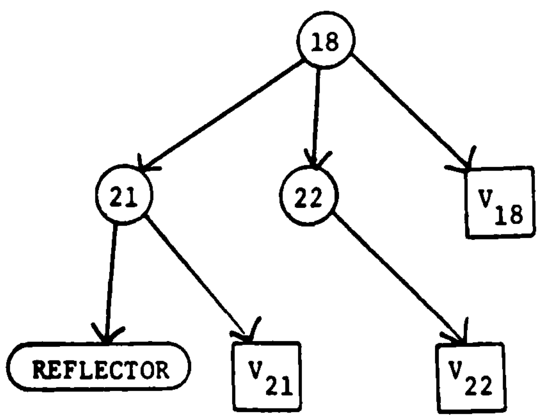
13. cap

17. plastic part
18. metal part
E. snap metal part into plastic part
E^{-1}. remove metal part



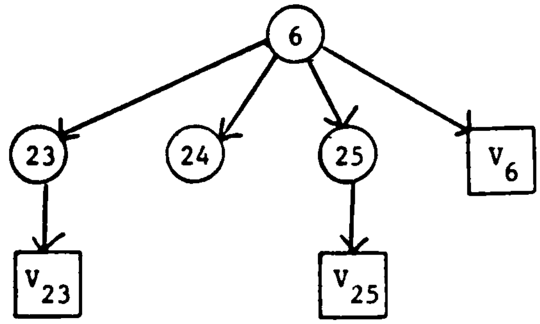
17. plastic part

19. plastic ring
20. transparent disc
F. put disc into ring
F^{-1}. remove disc from ring



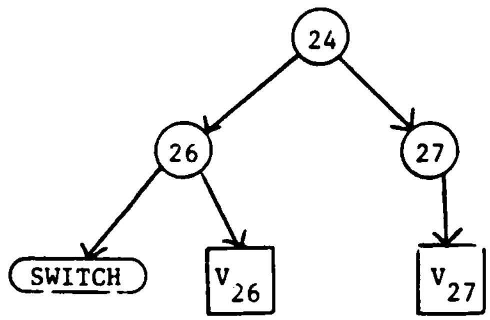
18. metal part

21. reflector
22. collar (nondetachable)



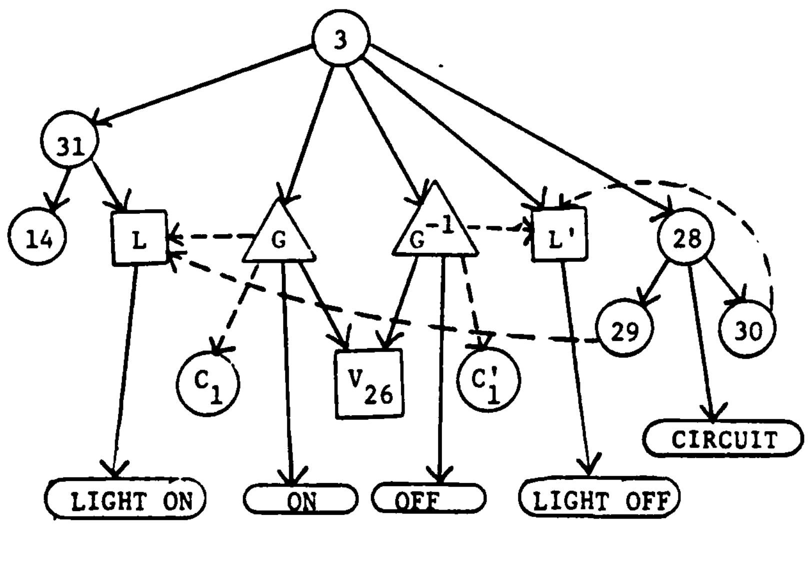
6. case

23. plastic tube
24. switch with contact bar
25. coil spring (nondetachable)
V_{25}. is seen only after removing batteries



24. switch with contact bar

26. switch
27. contact bar (nondetachable)
V_{27}. is seen only after removing batteries



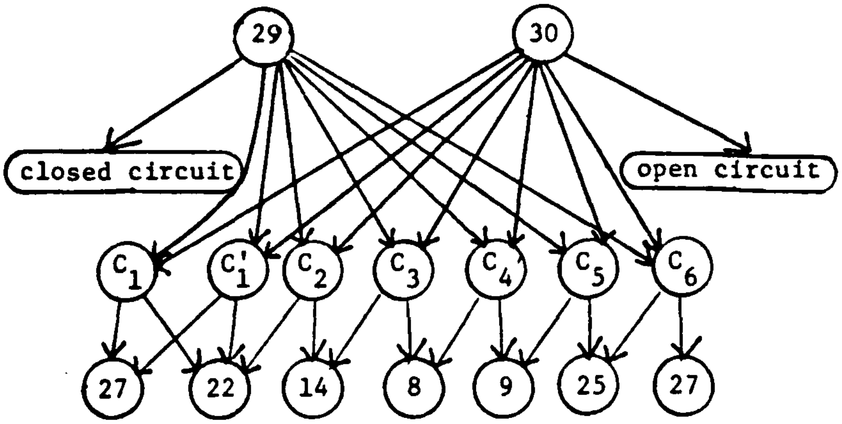
3. functionality

14. bulb
28. electric circuit
29. closed circuit
30. open circuit
31. lighted bulb
L. light is on
L'. light is off

G. push switch forward

G^{-1}. push switch backward

C_1. electrical connection; see 29. and 30. below
C_1'. lack of electrical connection; see 29. and 30. below.



29. closed circuit
30. open circuit

25. spring
27. bar
22. collar
14. bulb
8. battery
9. battery

C_1. bar is connected to collar
C'_1. bar is not connected to collar
C_2. collar is (electrically) connected to bulb
C_3. bulb is connected to battery
C_4. battery is connected to battery
C_5. battery is connected to spring
C_6. spring is connected to bar

C_2 is made by C.

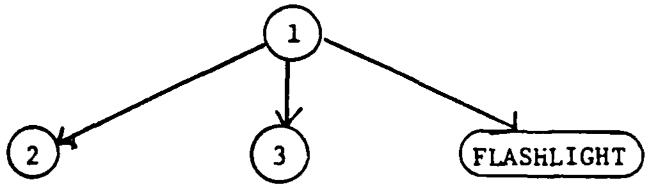
C_3 is made by A.

C_4 and C_5 are made by B.

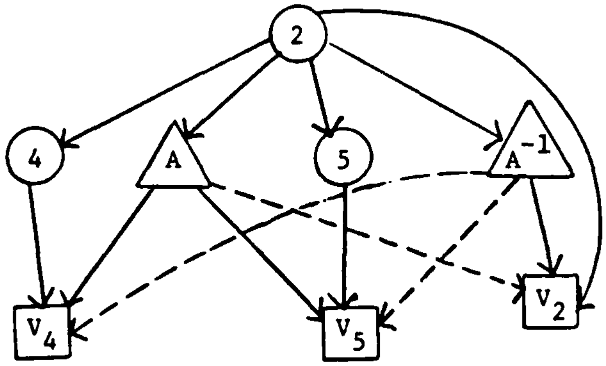
C_6 should be permanent

APPENDIX 2

The 7 diagrams below (on pages C1 through C3) represent a fictitious child's conceptualization of a flashlight.



1. flashlight
2. structure
3. functionality

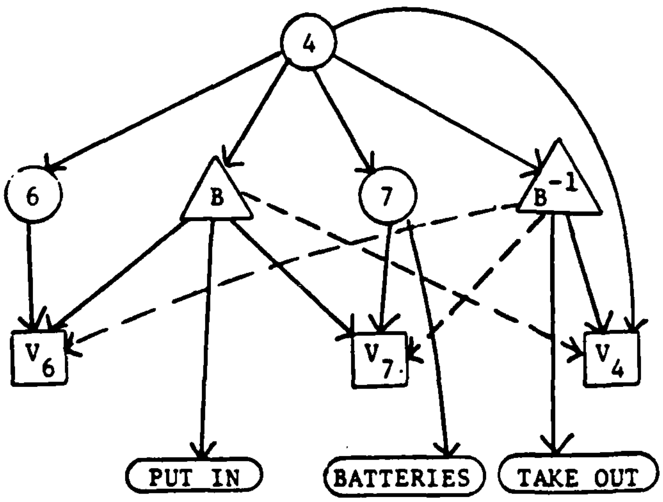


<u>2. structure</u>

4. case with batteries
5. front part with protector and bulb

A. screw on cap

A^{-1}. unscrew cap

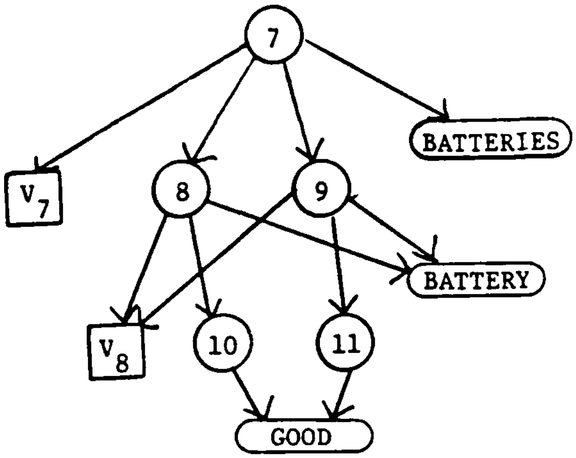


<u>4. case with batteries</u>

6. case
7. batteries

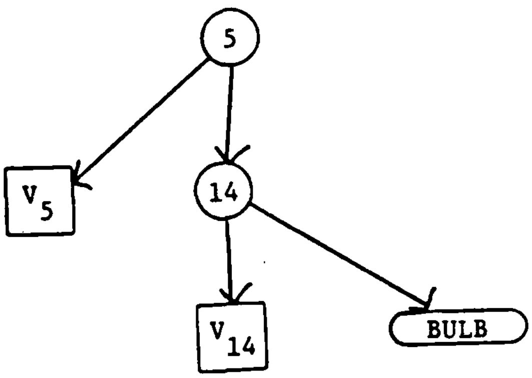
B. put batteries in

B^{-1}. take batteries out



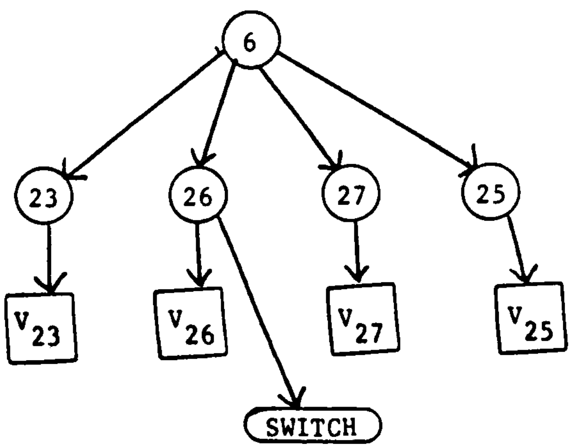
7. batteries

8. one battery
9. another battery
10 and 11. each battery is good
$V_9 = V_8$ because the batteries are visually identical



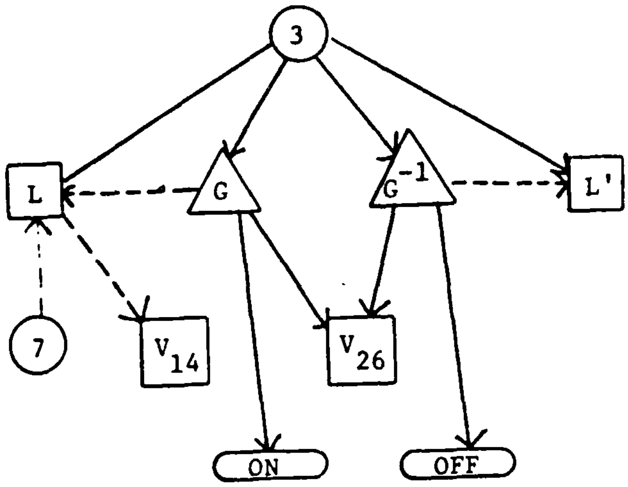
5. front part with protector and bulb

14. bulb



6. case

23. plastic tube
26. switch
27. bar
25. coil spring



3. functionality

L. light is on
L'. light is off
G. push switch forward
G^{-1}. push switch backward
7. batteries (good)

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