

# Acquisition of Operational Design Knowledge from Designed Objects Using Explanation-Based Learning Method<sup>†</sup>

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An EBL-based method for acquiring conceptual design knowledge in physical systems was proposed and implemented to a system based on the idea that such knowledge can be acquired by analyzing the structural features of existing artifacts. Since any artifacts can be interpreted via various design rationalities such as teleological, causal and economical ones, it can be modeled as a hierarchy which consists of designs goals, subgoals, structures and substructures toward attaining those goals. This results in a generalized version of Functional Diagram used in Value Engineering. From the Functional Diagram, general design knowledge of various levels can be acquired by a single positive instance of designed objects. The operability of the acquired knowledge is then analyzed with reference to its modes of acquisition. The acquisition method is implemented to a system using PROLOG.

**Key Words:** explanation-based learning, value engineering, functional analysis, operability of knowledge, acquisition of design knowledge

## 1. introduction

For supporting design processes by using computers, several kinds of CAD systems has been developed so far, but the so-called “conceptual design process” is still dependent on expertise of designers, thus it is required to develop computer-aided “conceptual design” systems.

It is generally acknowledged that a detailed analysis of existing artifacts is beneficial not only for the improvement of the artifacts in question but also for the creation of new ones. **Value Engineering** introduced by Miles provides a systematic method of analysis for deducing these improvements and new designs<sup>1)</sup>, which focuses on the functional composition of artifacts and the structures supporting these functions. This analysis, called “**Functional Analysis**”, enables us to deduce various new ideas for improving.

In this paper, by introducing the notion of “functional analysis”, we will discuss a “knowledge acquisition

method” which analyzes structural appearance of design examples in order to extract various pieces of design knowledge. The knowledge are then generalized to be operational for the conceptual design processes.

The difficulty of knowledge information processing in conceptual design processes stems mainly from the following three facts, i.e., (1) the relevant knowledge cannot be enumerated, (2) we need not only heuristics but also deep knowledge such as physical and/or mathematical principles (laws and effects), and (3) conceptual design itself is highly creative, thus most of the expertise for conceptual design cannot be described explicitly.

These facts imply that the examination of “**operationality of knowledge**” is crucial for supporting conceptual design processes<sup>2)</sup>. For knowledge of the conceptual design, we will introduce three kinds of operationalities, i.e., “applicability” to design phases, “rationality” and “efficiency” of design knowledge. These operationalities of the acquired knowledge will be discussed in relation to the modes of acquisition.

In our method of acquiring operational design knowledge, the relevant domain theories for design are hierarchically organized in relation to the “applicability” as shown in the left part of the **Fig. 1**. This organization is utilized to analyze design examples and to acquire design knowledge which are operational in each design phases. The domain theories are then refined to be “rational” via the processes of “functional analysis”. Based on an EBG (Explanation Based Generalization) method<sup>3)</sup>, this

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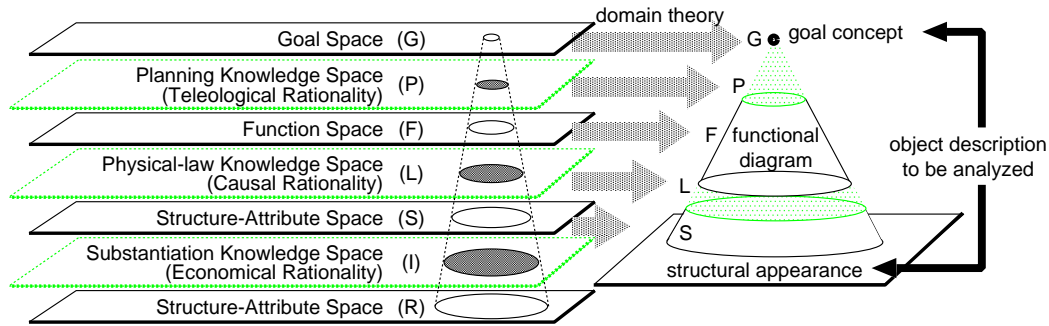
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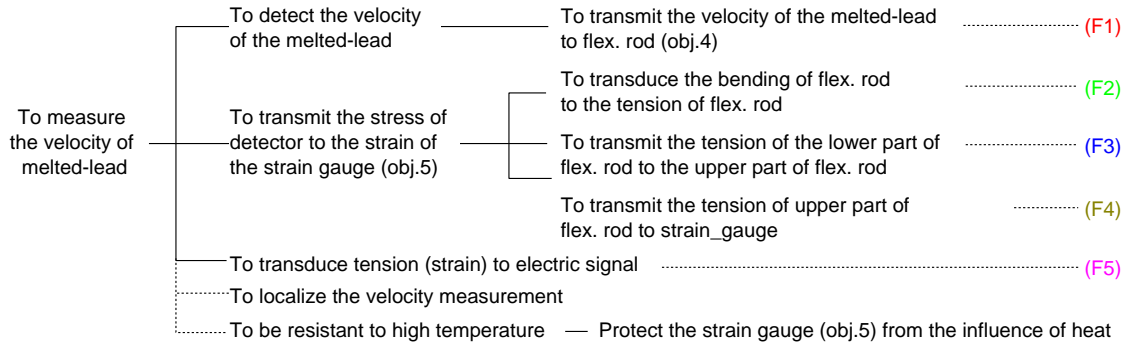
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**Fig. 1** Hierarchical knowledge representation of artifact and its relation to the domain theory of Explanation Based Learning



**Fig. 2** Functional Diagram of the flexible rod

refinement process is done with an aid by a computer system which is implemented by using the logical programming language PROLOG.

## 2. Functional Analysis of Design Examples and Design Knowledge

### 2.1 A Brief Introduction of Functional Analysis

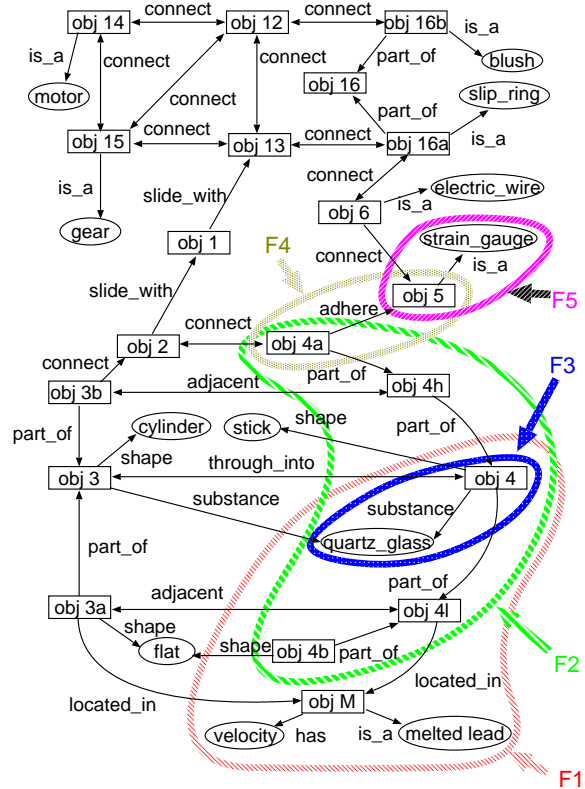
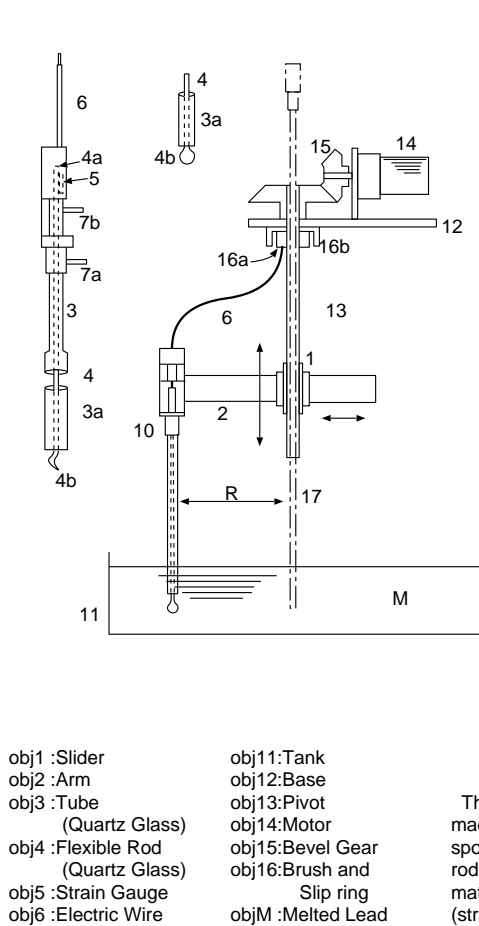
In Value Engineering, the “Functional Analysis” technique analyzes how the design goal (the primary function) is attained by the use of functional and structural composition of design examples (artifacts). The analysis results in the so-called “Functional Diagram” on which basis we can improve the artifact in question by searching for better structural components or a completely new structural composition. By focusing on the functional composition of the artifact, the modification or structural alteration is not constrained by the existing structural composition or by the components of the artifact.

**Fig. 2** shows the Functional Diagram of a sensing device shown in **Fig. 3** which is used to measure the velocity of melted lead<sup>4</sup>). This diagram shows that the primary function, “to measure the velocity of melted lead,” consists of three subfunctions, “to detect ...”, “to transmit ...” and “to transduce ...”, and that the second subfunc-

tion also consists of three primitive subfunctions F2, F3 and F4. Each primitive subfunction is supported by a set of structural entities. For instance, each of the leaves F1 - F5 of this diagram is attained by a substructure of the device as shown in the semantic network in the right part of **Fig. 3**. This network represents structural features of the sensing device shown in the left half of **Fig. 3**. The rectangular nodes in the right half of the figure represent primitive structural components that are linked by labeled linkage relations to each other. Ellipsoidal nodes represent the associated attribute values.

### 2.2 Functional Diagram and Design Knowledge

Even though the pieces of knowledge embedded in the Functional Diagram concerning the functional composition of artifacts, structural composition and function-structure relationships may be beneficial to the improvement of the artifacts analyzed, they lack generality i.e., they cannot be utilized for their improvement nor novel design of artifacts. This is because the Functional Diagram is strictly dependent on (1) the particular artifact analyzed and also on (2) the particular way how it is derived, i.e., it is dependent on the particular method used in the functional analysis and also on the person or the group of people who derived it.



The velocity of melted lead (M) is measured as follows: A flexible rod (4) is made of quartz glass whose upper end (4b) is supported by the arm (2). The spoon-like lower end (4a) is placed in M, so that the mass flow of M bends the rod producing tension on its surface, since the rod is made of an elastic material. Finally, the strain gauge (5) attached to 4b transduces tension (strain) as an electric signal.

Fig. 3 Structure of the flexible rod for measuring velocity of melted lead

In order to solve problem (2), a systematic method, called **FAST** (Functional Analysis System Technique)<sup>5)</sup>, was proposed. Even by the use of this method, a need still exists for standardizing the representation of the Functional Diagram<sup>6)</sup>.

### 3. A multi-layered model of artifacts and an EBL method for acquiring design knowledge

#### 3.1 Introducing EBL for Acquiring Design Knowledge

In order to solve problems (1) and (2), we will introduce a method based on an **EBL** (Explanation-Based Learning)<sup>3)</sup> to the Functional Analysis.

Given a “goal concept” and its single positive instance (“training example”), EBL try to explain how the training example satisfies the goal concept by referring to the “domain theory”. The explanation results in an “explanation tree” which is then generalized as far as the attainment of the goal concept is guaranteed. Any subtree of the generalized explanation tree can be chunked into a description

of a general piece of knowledge which shows that the conjunction of leaves is one of the sufficient conditions of the root of the tree.

By the use of this method, Functional Analysis can be done in a quite systematic way, and the resultant Functional Diagram contains all the essential knowledge on design, i.e., it shows a “general” way for attaining the primary function. In our method, the structural appearances of a design example are encoded into a semantic network as shown in Fig. 3, which is generalized by the so-called “irrelevant feature elimination”<sup>7)</sup> and by the “identity elimination”<sup>7)</sup>.

We adopted a two-step strategy for acquiring design knowledge. The first step produces a standardized and generalized Functional Diagram from which, in the second step, various types of operational design knowledge are then extracted.

#### 3.2 Hierarchical Model for Representing Artifacts

From the above perspective of Value Engineering, the process of design can be interpreted as a successive se-

lection of “ends” and “means” which correspond to design goals (primary functions), subfunctions, and substructures such as primitive components, materials, etc..

This selection process can be conceived by three types of **rationalities**: teleological, causal, and economical<sup>8)</sup>, as follows:

**Teleological Rationality:** the rationality on the selection of the functional composition of design.

**Causal Rationality:** the rationality on the selection of the structural composition of design for attaining the subfunctions.

**Economical Rationality:** the rationality on the selection of the substantial entities for realizing the structural composition of design.

In order to explain these rationalities of artifacts, we will need the following kinds of domain-specific knowledge:

**Planning Knowledge -Knowledge on Teleological Rationality:** knowledge on how to attain a goal (primary function) by combining subgoals (subfunctions).

**Physical-Law Knowledge -Knowledge on Causal Rationality:** knowledge on causal laws which may be used to explain the sufficiency of a substructure for attaining a subfunction.

**Substantiation Knowledge -Knowledge on Economical Rationality:** knowledge on the selection of substantial entities, for example, knowledge on cost, properties of materials, etc.

As shown in Fig. 1, Planning Knowledge (P) mediates (relates) a certain set of possible primary functions (Goal Space: G) with a certain set of possible functions (Function Space: F). Physical-Law Knowledge (L) mediates Function Space with a certain set of possible structure-attributes (Structure-Attribute Space: S). Substantiation Knowledge (I) mediates Structure-Attribute Space and a certain set of possible substantial entities (Substantial Entity Space: R).

### 3.3 Domain Theory for EBL

According to the above mentioned seven knowledge spaces (G, P, F, L, S, I and R), domain-specific knowledge (Domain Theory) for design, with which an EBL system yields a generalized form of Functional Diagram, can be organized. In the following, we will confine ourselves to the case of conceptual design of sensing devices<sup>9)</sup>. Hence, we will not consider the Substantiation Knowledge (I) or Knowledge on Substantial Entities (R).

The Domain Theory of this EBL system, illustrated in the right half of Fig. 3, consists of five kinds of knowledge as follows:

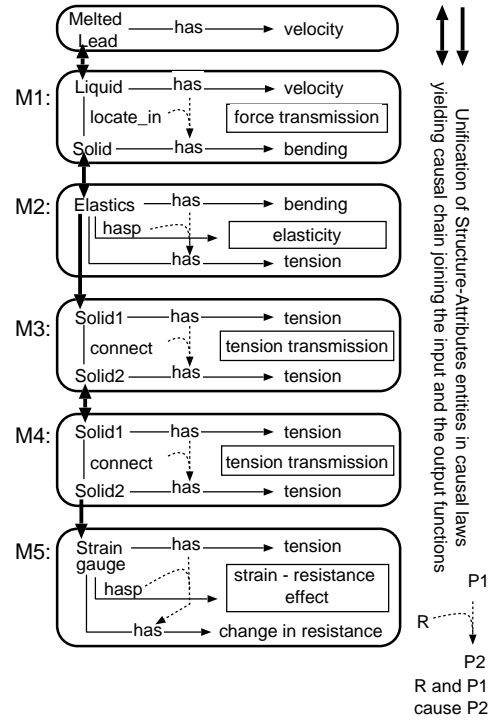


Fig. 4 Causal chain explanation of the measurement of fluid velocity

### Goal Space (G):

The goal of sensing devices is to measure the amount of specified physical quantity together with auxiliary goals such as “being adapted to the environment,” etc. In the above example, the goal is not only to measure the velocity but also to be resistant to high temperature and to localize the velocity measurement.

### Physical-Law Knowledge Space (L):

The process of measuring physical quantities usually consists of causal chains of physical laws. Fig. 4 shows the causal chain of the example (Fig. 3).

The causal chain consists of causal laws (M1~M5) which provide the base of each leave of the Functional Diagram (Fig. 2: F1~F5). Causal laws are given as general knowledge<sup>(1)</sup>, and they are specified in terms of the design example and linked to be the causal chain, which explains the way of measurement.

For example, both of the variables in Fig. 4: *Solid* (M1) and *Elastics* in (M2) are specified (instantiated) to *obj4a* in the design example in Fig. 3, then M1 and M2 are linked to form a part of the chain.

### Function Space (F):

Functions which are common to the area of sensing de-

(1) The general form of causal laws are encoded into Horn-clauses.

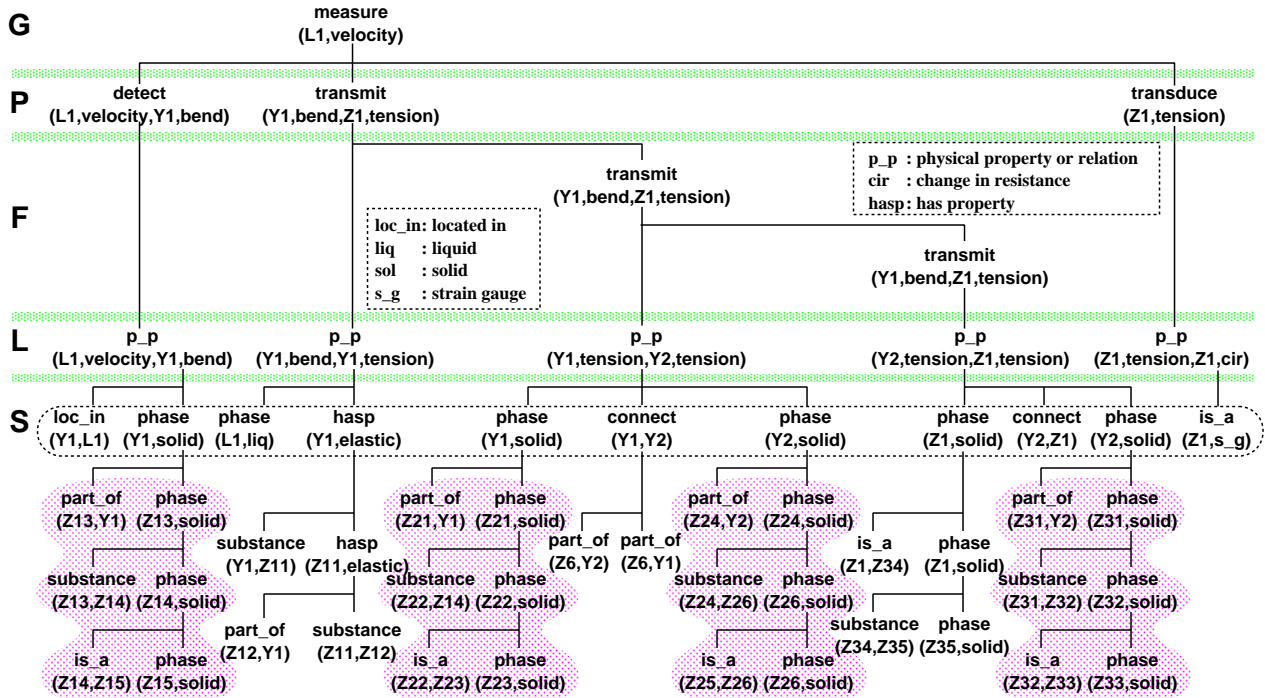


Fig. 5 Generalized Functional Diagram generated by the proposed EBL system

vices are “to detect”, “to compare”, “to balance”, “to transmit”, “to transduce”, etc.

**Planning Knowledge Space (P):**

As shown in Fig. 4, a physical causal chain is established when a primary function (G) is attained. As mentioned above, the constituents of the chain are originally given as fragmentary pieces of general knowledge, and they are specified to the artifact in question and linked to form a chain. Examining infinite number of combinations of these knowledge is practically impossible, therefore some plans which guide the combination are required even though they are dependent on particular domains.

One of the typical plans for measuring a physical quantity (P of X) is to detect P as a physical quantity Q of Y and then to transmit Q to a transducer (Z) which then transforms Q into a quantity (R) of prespecified type such as an electric current, voltage, etc.

Another typical one is to balance and to compare it with a standardized quantity and then to transform their difference into a specified type of quantity.

**Structure-Attribute Space (S):**

We use semantic network representation of the structures and of the attributes of sensing devices, as shown in Fig. 3, which enables the inheritance of attribute values through “is-a” or “part-of” relations.

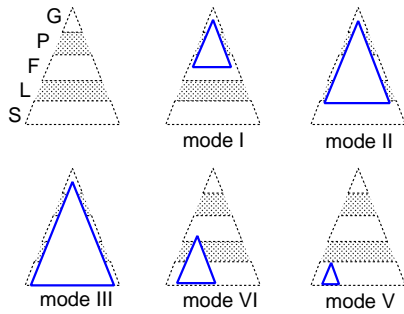
**4. Acquisition of operational knowledge by EBL method**

**4.1 Generating and generalizing Functional Diagram**

In this section, we will discuss a way for supporting knowledge acquisition from structural descriptions of design examples (artifacts).

The inputs to the proposed EBL system are the semantic network representation of the structure of a sensing device (Fig. 3) and its primary function. The system derives the explanation tree, which shows the way how the primary function is attained by the use of plans, subfunctions, physical-laws, structure-attributes, by referring to the domain theory in the left half of Fig. 1. This explanation tree is then generalized by filtering out unnecessary terms which have no use in attaining the primary function (“irrelevant feature elimination”) and by generalizing terms which are dependent to the particular artifact in question (“identity elimination”). The inference system is implemented by modifying and extending a PROLOG-based EBG method<sup>10),11)</sup>. We will hereafter call the resultant diagram (tree) a **Generalized Functional Diagram (GFD)**.

Fig. 5 shows the GFD obtained by our EBL system for the sensing device shown in Fig. 3. Compared with the manually-made diagram in Fig. 2, the new diagram



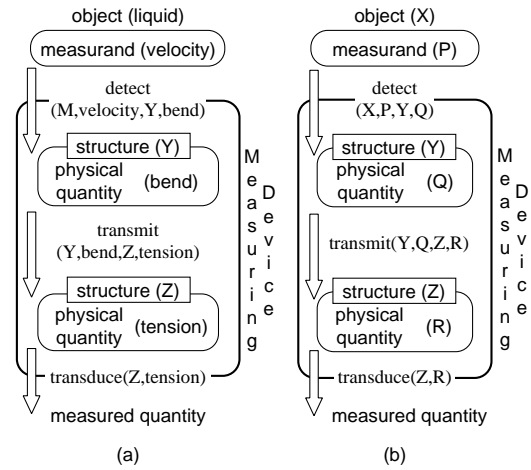
**Fig. 6** Five modes of knowledge acquisition from Generalized Functional Diagram

is more systematic and standardized. It contains all the necessary information for the measurement and no other surplus information. In the figure, “transmit(Y1, bend, Z1, tension)” shows that the amount of bending in the structural component Y1 is transmitted to the amount of tension in component Z1. (The system is implemented by PROLOG where capital letters represent variables.) Also, the new diagram contains more general information on how to measure fluid velocity “in general,” and is not confined to measurement of melted lead. Moreover, it should be noted that the terms (arguments of “p-p”) located in space L constitute a “causal chain” joining from (L1,velocity) to (Z1,cir) whose existence are supported by the terms in space S.

**4.2 Modes of knowledge acquisition from Generalized Functional Diagram**

The **GFD** has a hierarchical structure which naturally reflects the hierarchy of the design knowledge in the left half of Fig. 1. This hierarchy corresponds to the boundaries of operability<sup>12)</sup> in the design knowledge embedded in the diagram in Fig. 5. We extract operational design knowledge from the **GFD**, by arbitrarily setting the “Goal Concept” (**GC**) to be explained and the “Level of Explanation” (**LE**) in the Diagram. It is well-known that appropriate selection of **LE** is important when applying EBL method<sup>13)</sup>. As shown in **Fig. 6**, the combination of **GC** and **LE** results in five modes of knowledge acquisition.

In Mode I, the **GC** is set to be the measurement of fluid velocity in general and the **LE** is set to be in the Function Space F. In this model, we obtain an associational knowledge which is a general planning knowledge for attaining the primary function. In other words, the associational knowledge relates the primary function to the component functions whose combination attains the primary function. Namely, by the EBL system, we can extract the general knowledge which is embedded implicitly



**Fig. 7** Acquired planning knowledge (b) for measuring liquid velocity, which can be regarded as a specialization of domain theory (a) in the Planning Knowledge Space

in the mediating spaces between **GC** and **LE**. The knowledge acquired is shown in **Fig. 7** (a). This knowledge turns out to be a specialization of the original planning knowledge (Fig. 7 (b)) prepared in the Planning Knowledge Space. Namely physical quantities P, Q and R in the planning knowledge are specified as “velocity” “bend (bending)” and “tension”, respectively, to constitute an operational knowledge whose causal rationality is assured by the causal chain.

Mode II (**GC** – measurement of fluid velocity, **LE** – the uppermost level in the Structure-Attribute Space S) yields the most general (abstract) structure (and attributes) for measuring fluid velocity. For example, from the flexible rod, one of the sufficient conditions for measuring fluid velocity is acquired as the conjunction of terms that are encircled by a broken line illustrated in Fig. 5.

In Mode III (**GC** – measurement of fluid velocity, **LE** – the lower-most level in Space S), we can acquire the most detailed (concrete) structure which reflects in fidelity the original structure of the input instance which is in contrast with Mode II. In the case of the flexible rod, the conjunction of all the leaves of **GFD** is acquired as one of the sufficient condition of **GC**.

Mode IV (**GC** – Function Space F, **LE** – Space S) yields the knowledge on the essential structural conditions for attaining various functions in the diagram. In the case of the flexible rod, when **GC** are set to the node “detect(L1, velocity, Y1, bend)” and **LE** is set to be the uppermost level in Space S, the acquired knowledge shows that “fluid velocity can be detected by the bend of a stick when its one end is dipped into the fluid”. Thus, we can acquire associational knowledge linking functions,

physical-laws and structure-attributes.

In Mode V (**GC**, **LE** – Space S), we can obtain knowledge on the structural modules which are common to various designs as shown in the shaded area in Fig. 5, which shows a “knowledge module” which explains that an object is solid.

#### 4.3 Applicability of Acquired Knowledge

The notion of operability of the acquired knowledge is one of the most important aspects of knowledge acquisition<sup>2)</sup>. The first notion of operability is the quality of acquired design knowledge which can be evaluated in relation to the “phases” of the conceptual design process. For example, the knowledge represented in functional descriptions, i.e., the definition of the **GC** or the general method for attaining the **GC** in terms of functional entities, is applicable to the functional design phase, and the knowledge in structural descriptions is applicable to the structural design phase.

Hence, knowledge acquired in Mode I is applicable to the functional design phase; those in Modes II and III are applicable to the structural design phase; that in Mode IV is applicable to searching for substructures which support subfunctions that are validated by the firm linkages among space F, L and S; that in Mode V is applicable to search for useful structural modules. Comparing modes II and III, the pieces of knowledge by mode II are more general than those by mode III, whereas the latter are more “efficient” than the former in the sense of advancing the design plans.

In general, the modes in an explanation tree (**GFD** are hierarchically organized, and hence, we will have various options on selecting the nodes for explanation. This freedom is utilized to extent EBG to plural training examples<sup>13)</sup>. The selection of nodes for explanation is thus a crucial problem in applying EBG. Thus we will need a method to confine the selection. The proposed five modes of knowledge acquisition are derived by confining the explanation level near the operability boundary. In Mode III, the definition of **GC** is given as the conjunction of the leaves of the **GFD** which are located at the bottom of **GFD**. In Mode II, on the other hand, it is given as the conjunction of the uppermost branches in Space S which are located above the leaves (lower-most branches). Hence Mode II provides more general and abstract knowledge whereas Mode III provides more detailed and concrete knowledge<sup>7)</sup>.

#### 4.4 Rationality of Acquired Knowledge

The second notion of operability is the quality of knowledge which can be evaluated in relation to what ex-

tent this a piece of knowledge is certified its usage. In this sense, we take “knowledge which requires certification of its usage by causal rationalities” not operational. In other words, even though its applicability is relatively narrow, a piece of knowledge which is certified its causal rationality is regarded to be operational.

As mentioned in Section 2.2, the acquired knowledge has teleological and/or causal rationalities when the mediating spaces P and/or L (Planning Knowledge Space and/or Physical-Law Knowledge Space) of these rationalities are located between the **GC** and the **LE**. It is quite difficult to prepare the domain theory in Space P beforehand such that it has causal rationalities; to do so we would have to examine a large number of cases of usage for each physical law. Hence, we have adopted an approach where the domain theory in Space P is rational only in the teleological sense. This knowledge becomes causally rational when compiled with the knowledge on Space L or S by the EBL process. For instance, the acquired knowledge (in Mode I) in Fig. 7(a) is causally rational, although it is derived from the planning knowledge prepared in Space P shown in Fig. 7(b) that is not necessarily causally rational.

#### 4.5 Efficiency of Acquired Knowledge

The third notion of operability is the “efficiency” of knowledge which can be evaluated by the amount of advancement of design processes when it is applied. Hence, it can be roughly estimated by the distance (depth) between the **GC** and the **LE**. For example, Mode III provides more efficient knowledge than Mode II, even though both of them provide the same sort of applicability and rationality. Also, Mode I provides less efficient one than Mode II. Mode IV provides more efficient one than Mode V and less efficient one than Mode III. Hence, we have the following comparisons:

$$III > IV > V$$

$$III > II > I$$

## 5. Conclusions

We have proposed a knowledge acquisition method for supporting conceptual design processes. The framework of this method consists of two steps, i.e., the first step analyzes a design example by using hierarchically organized domain theories and produces a standardized and generalized Functional Diagram from which, in the second step, various types of operational design knowledge are then extracted. Each extracted knowledge reflects domain theories and the information of the analyzed artifact. In other words, the proposed method is a hybrid

system of “deductive learning” and **SIG** (Single Instance Generalization). It is well-known that this kind of framework elucidated several problems. For example, knowledge acquisition system requires its own knowledge, and the acquired knowledge is not a “novel” one but a combination of prepared knowledge, and so on. In order to solve these problems, we discussed the operability of knowledge and pointed out that the fundamental difference between the prepared knowledge (domain theory) and acquired knowledge is the “rationality” of its usage. The prepared knowledge should be as general as possible, therefore their rationality of usage are not certified. It may be noted that over generalization of domain theory leads to lose the ability to guide the SIG processes.

We employ the Horn-clause form for encoding domain theory at the present stage, but we are now investigating some other representational schemes of knowledge, e.g., determination rule<sup>14)</sup> which is more general and more easy to encode design knowledge.

We also introduced some modes for extracting operational design knowledge from a single instance of artifacts, and clarified the quality of acquired knowledge with reference to its modes of acquisition.

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