PUTTING FUNCTIONAL KNOWLEDGE ON FIRMER GROUND

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In this paper we focus on the concept and representation of function in the context of the multimodeling approach. The main contribution of the paper is to discuss the nature of functional knowledge and to disambiguate this type of knowledge from other types, such as teleology, behavior, and structure. Moreover, a general and theoretically sound framework for integration of these types of knowledge into a coherent system is proposed. Existing approaches to the definition and the representation of function are compared and their major limitations are highlighted. The concept of function and its representation in the multimodeling approach are illustrated. An example of functional representation concerning a household electric buzzer is discussed and the relations between functional knowledge and teleological, behavioral and structural knowledge are presented. The main contributions of our approach in the domain of diagnostic reasoning are summarized, and the paper concludes by mentioning current research work.

DEFINING AND REPRESENTING FUNCTION: EXISTING APPROACHES

The concept of function enters into a system description when some teleology (i.e., purpose) is supposed to be accomplished by the system (Kampis, 1987). A crucial point however, concerns the precise differentiation of the two concepts of function and teleology. Two main points of view can be found in the literature. For some authors, the concepts of function and teleology are synonymous: the function of a system is identified by the task the system accomplishes or should accomplish (Steels, 1989) or by its intended use or purpose (de Kleer, 1984; Sembugamoorthy & Chandrasekaran, 1986; Keuneke & Allemang, 1989; Franke, 1991; Keuneke, 1991; Sticklen & Bond, 1991). Other authors distinguish more accurately between function and teleology by defining function as (1) a relation between the goal of human user and the behavior of a system (Bobrow, 1984), or (2) binding information that relates components to processes in which they take part (Addanki & Davis, 1985), or (3) abstract characterization of behavior performed by taking into account

A preliminary version of this paper was presented at the AAAI-93 Workshop on Reasoning about Function, held in Washington, D.C., on July 11, 1993.

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Applied Artificial Intelligence, 8:239–258, 1994

0883-9514/94 $10.00 + .00

the purpose of a system, namely, the reasons of actual implementation (focusing on overall organizational principles) (Rasmussen, 1986), or (4) interpretation of behavior that captures typical properties of components in terms of generalized actions performed on substances (e.g., information, energy, mass) flowing through them (Lind, 1982; Fink & Lusth, 1987).

Both points of view conceive function as more abstract than behavior and structure, where abstraction is intended as independence from physical implementation (different structures may provide the same function) (Bobrow, 1984; Rasmussen, 1986; Fink & Lusth, 1987) or as change in the conceptual level (for example, when sequences of states or pieces of behavioral trajectories that produce a synergistic uniform action are "packed" together and identified with a new higher-level concept, e.g., oscillation or amplification).

Two main approaches, which we will informally name "hybrid" and "pure," have been followed in representing the function of a system. In the hybrid approach, different types of knowledge about the system (i.e., structural, behavioral, functional, and teleological) are organized in a single frame, which is usually centered on teleology. As an example, Figure 1 shows the functional representation of the reaction wheel assembly (RWA) onboard the Hubble space telescope as proposed by Goel and Chandrasekaran (1989). This functional representation specifies the purpose of the system (*to_make*), the input state (*provided*), and the contextual conditions (*given*) to be met in order to achieve the purpose, the behavior that realizes the purpose (*by*), and the undesired effects (*side_effect*) expressed both in abstract (e.g., generation of heat) and behavioral terms (*by*). Figure 2 sketches the general frame upon which this representation is based.

In the hybrid approaches the modeler is free of packaging knowledge inside the given frame and establishing relations between knowledge elements of different types without obeying strict modeling constraints. Although, on the one hand, these approaches simplify the modeling process, on the other hand; (1) they lack a principled methodology for model building, (2) they do not easily allow automatic checking of consistency between different types of knowledge in the model, (3) they

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FUNCTIONS:
 GIVEN: Control signal c
 TO-MAKE: Change angular momentum of Telescope
          L_telescope
          | ΔL_telescope | = f(+c)
 PROVIDED: Large Angular Velocity of Rotor
 BY: BehaviorChangeMomentum
 SIDE-EFFECT: Generation of heat in Bearing
              Q_bearing
              Q_bearing = f(-|Ω_shaft|)
              BY: BehaviorGenerateHeat
END FUNCTIONS
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Figure 1. Hybrid approaches: functional representation of the reaction wheel assembly (Goel & Chandrasekaran, 1989).

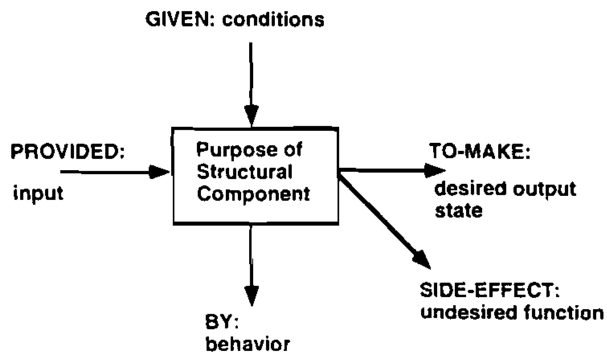

Figure 2. Hybrid approaches: a general frame.

lead to monolithic models that are difficult to reuse, and (4) they do not allow use of each type of knowledge (e.g., structural, behavioral, or functional) in isolation to perform complex tasks (such as simulation or diagnosis).

In the pure approaches, function is clearly separated from other types of knowledge. It is represented by means of a set of primitives, which are interpretations of typical behaviors of physical systems. As an example, Figure 3 shows the set of primitives proposed by Lind (1982), while Figure 4 illustrates the functional representation of a reactor coolant system in terms of this set of primitives. In this approach, functional primitives describe primitive actions that a component may perform on substances flowing through it; for example, the storage represents the property of a system to act as a buffer or accumulator of mass or energy.

However, a crucial problem in pure approaches is the choice of the set of functional primitives. In general, primitives are chosen empirically, by observation and generalization of specific systems' behaviors. This leads to two main difficulties: there is no guarantee that the set of primitives is still expressive outside the class of observed systems and (2) the link between behavior and function has no formal physical basis; thus, the minimality of the set is hard to evaluate, and automatic checking of consistency between different models becomes a difficult or even impossible task.

In order to overcome the above described limitations of current approaches to functional representation, we claim that the chosen approach should be pure, but physically sound.

FUNCTION IN THE MULTIMODELING APPROACH

In recent years, we proposed a novel methodology for representing and reasoning about physical systems, called multimodeling (Chittaro et al., 1989, 1992, 1993a; Brajnik et al., 1990). This approach is based on the key idea of considering the task of reasoning about a physical system as a cooperative activity, which exploits the

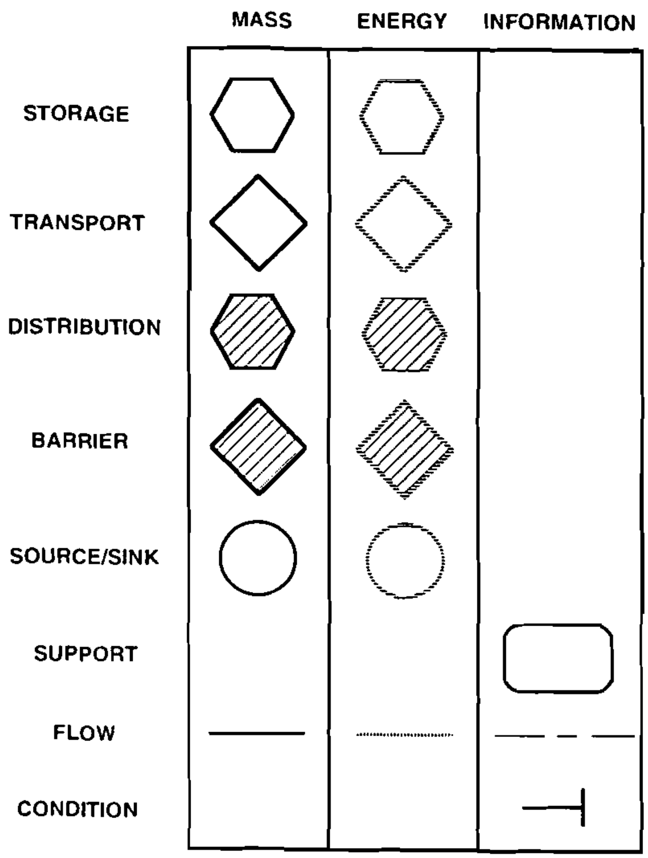

Figure 3. Pure approaches: a basic set of roles (Lind, 1982).

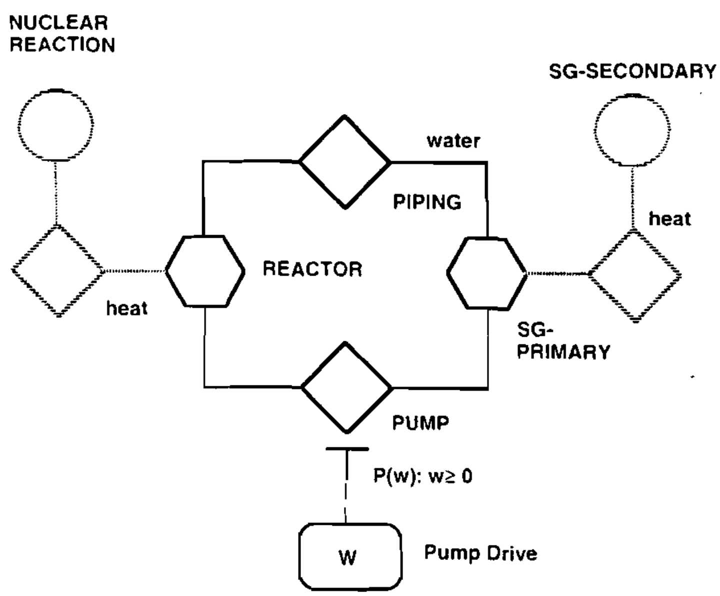

Figure 4. Pure approaches: functional representation of a reactor coolant system (Lind, 1982).

contribution of several separate models of the system, each one encompassing only a specific type of knowledge and a specific representation mechanism. Moreover, models are interconnected, that is, any individual model must be explicitly and appropriately connected to the others. The execution of a problem-solving task (e.g., diagnosis or design) within the multimodeling approach is based on two fundamental mechanisms: (1) reasoning *inside* a model, which exploits knowledge available within a single model by using model-specific problem-solving methods, and (2) reasoning *through* models, which supports opportunistic navigation among models in order to allow each individual step of the problem-solving activity to exploit the most appropriate knowledge source. A detailed description of representation and reasoning issues in the multimodeling approach is given by Chittaro et al. (1993a). For the purpose of this paper, we are mainly concerned with the concept of epistemological type.

Epistemological Types

By epistemological type, we mean the class of epistemological features the model can represent about the real system. In our approach we consider five epistemological types:

Structural knowledge is knowledge about system topology. This type of knowledge describes which components constitute the system and how they are connected to each other (their adjacency).

Behavioral knowledge is knowledge about potential behaviors of components. This type of knowledge describes how components can work and interact in terms of the physical quantities that characterize their state (variables and parameters) and the laws that rule their operation.

Functional knowledge is knowledge about the roles components may play in the physical processes in which they take part. This type of knowledge relates the behavior of the system to its goals, and deals with functional roles, processes, and phenomena.

Teleological knowledge is knowledge about the goals assigned to the system by its designer and about the operational conditions that allow their achievement through correct operation. This type of knowledge concerns the high-level reasons that are behind the system concept and that have determined its actual structure.

Empirical knowledge is knowledge concerning the explicit representation of system properties through empirical associations. This type of knowledge may be derived from observation, experimentation, and experience and may include, in particular, the subjective competence that usually human experts acquire through direct interaction with a system.

The five epistemological types defined above can be appropriately grouped into three categories. Structural and behavioral knowledge are fundamental knowledge used to reason about a system exploiting the objective and neutral language of natural sciences. Functional and teleological knowledge are interpretative knowledge derived from a subjective interpretation of fundamental knowledge in terms of functions and goals of system components. This knowledge does not have the same generality and objectivity of fundamental knowledge; for example, when we say "component X is devoted to . . . ," we express a relationship between a system component (its structure and behavior) and a goal, which is generally not valid for other components of the same type in the same system or in other systems. Finally, empirical knowledge is a separate category that concerns explicit statements of system properties and may refer to both fundamental and interpretative knowledge.

In the following, we will examine the concept of function and its representation in the multimodeling approach.

Functional Representation

The function of a system is defined as the relation between its behavior and the goals (teleology) assigned to it by the designer. The functional representation of a system is aimed at describing how the behaviors of individual components contribute to the achievement of the goals assigned to each part of the system (Rasmussen, 1986).

Functional knowledge is represented through three kinds of models: the model of functional roles, the model of processes, and the model of phenomena. These models are related by well-defined links. In this way, the mapping between behavior and teleology is realized in a gradual way by progressively introducing in the representation knowledge elements that are more and more dependent on purpose. We will briefly sketch the three kinds of models in the following and then we will illustrate the links existing among them.

Functional Role Model

We interpret the behavior of a system in terms of flow structures that is, in terms of networks of operators acting on sub. tances flowing through the structure of the system (e.g., electrons, heat, liquids) and in terms of the causes responsible for their flow (e.g., electrical voltage, thermal gradient, pressure gradient).

In this framework the functional role of a component is an interpretation of its behavior, or more precisely, of the equations governing its behavior, and is aimed at characterizing how the component contributes to the realization of the flow structure in which it takes part.

The interpretation is carried out using the tetrahedron of state (TOS) (Paynter, 1961; Rosenberg & Karnopp, 1983). The TOS (as shown in Figure 5) is an abstract framework that describes a set of generalized equations common to a wide variety of domains (such as thermodynamics, rotational and translational mechanics, fluid

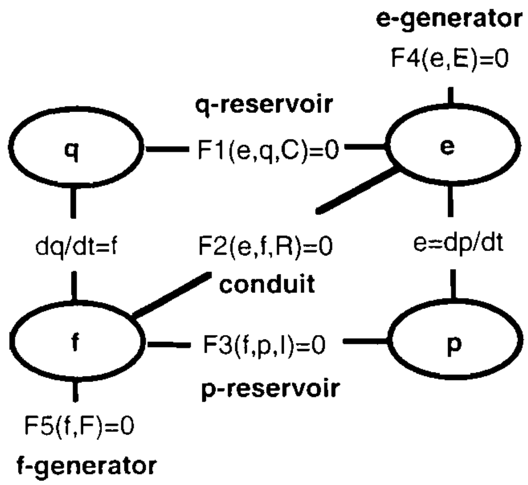

Figure 5. The tetrahedron of state (Paynter, 1961) and the associated names of functional roles.

dynamics, and electromagnetism). Generalized equations describe typical relations among a set of generalized variables, such as effort (e), flow (f), impulse (p), and displacement (q), and generalized parameters, such as capacity (C), resistance (R), inductance (I), electro-motive force (E), and electromotive flow (F). When the TOS is instantiated in a specific domain, we obtain the ordinary physical variables and equations.

The set of primitive functional roles has been chosen by assigning a name (q-reservoir, p-reservoir, conduit, e-generator, f-generator) to each generalized equation. The conduit role has been further specialized in order to highlight special cases, such as infinite resistance (barrier role) or infinite conductance (purely conductive conduit). In this way, the choice of functional roles has a sound basis. Functional roles have clear semantics that can be checked by looking at the form of the generalized equation that they are an interpretation of. A modeling guide is available to the modeler. The set of functional roles is defined independently of any specific domain and has a wide applicability.

Two types of relations between functional roles have been identified by looking at the possible ways that generalized variables may influence each other. These are mutual dependency and influence. Two functional roles FR_i and FR_j, which refer to physical equations PE_i and PE_j, respectively, are *mutually dependent* if PE_i and PE_j share a physical variable directly or indirectly [i.e., through a structural equation, which is a relation among physical quantities that does not involve parameters and usually represents general principles of conservation (balance equations) or definitions of new concepts (definitional equations)]. Figure 6*a* shows an example of mutual dependency (direct) between two conduit roles associated with two electrical resistors connected in series (they share the I variable); Figure 6*b* shows an example of mutual dependency (indirect) between two reservoir roles, one associated with

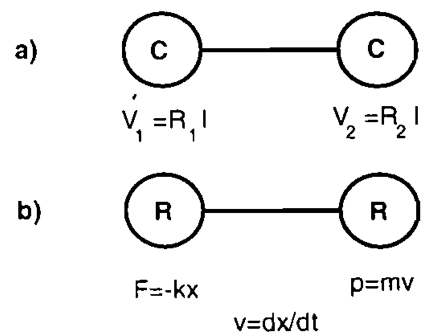

Figure 6. Examples of mutual dependencies.

the spring and one with the mass of an oscillating system (the definitional equation $v = dx/dt$ relates variable x in one role to variable v in the other).

A functional role FR_i that refers to physical equation PE_i *influences* a functional role FR_j that refers to physical equation PE_j if a physical variable of PE_i is a parameter of PE_j. Figure 7 shows an example of influence between a reservoir role associated with a tap and a conduit role associated with a pipe (the amount of angular displacement θ stored in the reservoir determines the value of resistance R of the conduit).

The functional role model of a system describes the potential functional roles of its components and the relations among them. It is represented by a functional role network (FRN). Of course, since functional roles and relations are generalized entities, they have to be specialized in the appropriate physical domains when they are used to represent a specific system.

Process Model

Functional roles participate in physical processes. A process is a four-tuple <cofunction, precondition, effect, posteffect>, where cofunction is a FRN that specifies which functional roles are necessary and how they must be related in order to enable the occurrence of the process; precondition is a logical predicate that characterizes the situation that enables the process to occur; effect is a logical predicate that characterizes the situation that is true during the occurrence of the process; and posteffect is a logical predicate that characterizes the situation that is true after the process has terminated, after its precondition ceases to hold.

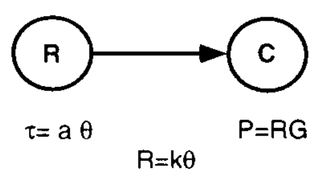

Figure 7. Example of an influence relation.

A finite set of three possible processes has been identified for the class of systems whose behavioral model can be interpreted in terms of the TOS. They are the transporting process (TRANS), the reservoir charging process (RESC), and the reservoir discharging process (RESD). These types of processes are described in detail by Chittaro et al. (1993a). For example, the cofunction of a transporting process can be constituted by a generator and an arbitrary positive number of conduits connected in series; its precondition can specify that the effort variable (i.e., voltage in the electrical domain, pressure in the hydraulic domain, force in the mechanical domain) associated with the generator is greater than zero; its effect can specify that the flow variable (i.e., current in the electrical domain, flow in the hydraulic domain, velocity in the mechanical domain) associated with the conduits is greater than zero; its posteffect can specify that the effort variable associated with the generator is zero. We have also introduced blocking versions of the three processes by including at least a barrier in their cofunction: for example, a transport-blocking process differs from a transporting process in that (1) its cofunction can be composed of a generator, an arbitrary number of conduits, and at least a barrier connected in series and (2) its effect specifies that the flow variable associated with the conduits is zero.

Instances of processes can be identified automatically by a pattern matcher once general patterns for possible cofunctions are defined. For example, the pattern matcher can analyze the functional role model to recognize instances of the general cofunction pattern described above for transporting processes; in this way, all possible transporting processes in the process model can be identified.

Processes have an associated functional state: active or not active. We say that a process is active if its cofunction holds in the system and its precondition is satisfied; the process is not active when either its cofunction does not hold or its precondition is not satisfied.

Three types of relations between processes have been identified by looking a the possible ways function roles are related. These are as follows:

Direct causation: A process P_i directly causes a process P_j if the effect or posteffect of P_i entails the precondition of P_j. For example, pumping (reservoir charging in the rotational domain) causes water transportation (transporting in the hydraulic domain), since the effect of pumping is to create a pressure drop, that is, the precondition for water transportation.

Regulation: A process P_i regulates a process P_j if there exists an influence relation between two functional roles belonging to their respective cofunctions that involves a generalized resistance. For example, the process of turning a tap changes the section of the water conduit and thus modifies the rate of the process of water transportation.

Support: A process P_i supports a process P_j if there exists an influence relation between two functional roles belonging to their cofunctions that involves a generalized substance on one side and a generalized capacitance (or inductance) on the other side. Consider, for example, two hydraulic tanks A and B connected through a pipe. Suppose that tank A has been filled with hot water, while B is empty, and that the hot water flows from A to B. Two processes coexist: process 1 is a discharging capacitor process in the hydraulic domain (water flows from tank A to B), and process 2 is a discharging capacitor process in the thermal domain (heat flows from A to B). We can now say that process 1 supports process 2 because of the influence relation holding between water and heat: the capacity of the water considered as a reservoir of heat is influenced by the volume of water present in the tank. The process model of a system describes the potential processes that may occur in the system and their relations. It is represented by a process network, where processes are specialized in the appropriate physical domains.

Phenomenon Model

Processes participate in the definition of physical phenomena. A phenomenon is a four-tuple <organization, precondition, effect, posteffect>, where organization is a process network that specifies which processes are necessary and how they must be related in order to enable the occurrence of the phenomenon; precondition is a logical predicate that characterizes the situation that enables the phenomenon to occur; effect is a logical predicate that characterizes the situation that is true during the occurrence of the phenomenon; and posteffect is a logical predicate that characterizes the situation that is true after the phenomenon has ended, that is, after its precondition ceases to hold.

Phenomena whose organization is constituted by a single process are called elementary phenomena. The set of phenomena is open ended. Several types of commonly occurring phenomena can be easily identified, such as natural and damped oscillation, homeostasis, and dynamic equilibrium. Phenomena are described in detail by Chittaro et al. (1993a).

The phenomenon model of a system describes the potential phenomena that may occur in the system and their relations. It is represented by a phenomenon network, where phenomena are specialized in the appropriate physical domains.

Integrating Functional Models

Well-defined relations exist between the functional role model and the process model of a system as well as between the process model and the phenomenon model. The link between the functional role model of a system and its process model is represented by the concept of cofunction, which aggregates a set of functional roles supporting a process. Analogously, the link between the process model of a system and its phenomenon model is represented by the concept of organization, which aggregates a set of processes supporting a phenomenon. In this way, it is possible to use each model separately but also to translate/reformulate data and results from one model to another.

CASE STUDY: MODELING A HOUSEHOLD ELECTRIC BUZZER

In order to illustrate the above concepts, let us consider the functional representation of a conventional door buzzer. The schema of the device is represented in Figure 8. It consists of a gong, a spring-loaded hammer, a contact, an electromagnet whose armature is connected to the hammer, a battery, and a switch. Although the buzzer is a relatively simple system from a structural point of view, its operation is complex enough to explore ideas of qualitative simulation and functional modeling (de Kleer & Brown, 1983; Sembugamoorthy & Chandrasekaran, 1985; Kumar & Upadhyaya, 1993).

Figure 9 shows the functional representation of the buzzer. It consists of a functional role model (FUN.R), a process model (FUN.P), a phenomenon model (FUN.PH), and two sets of links (represented within boxes) relating corresponding elements in different models. Several assumptions have been made in building these models. For example, we ignored thermal effects of current flow as well as any current that may be induced by the magnetic field of the coil. Moreover, we neglected the reluctance of iron in the magnet. These assumptions are reflected in the choice of the roles, processes, and phenomena included in the representation.

Considering Figure 9, the function of the door buzzer can be understood as follows. When the user acts as a generator of mechanical force (GO) on the switch (RO^q), he/she enables a reservoir charging process ($RESCO^q$) of mechanical

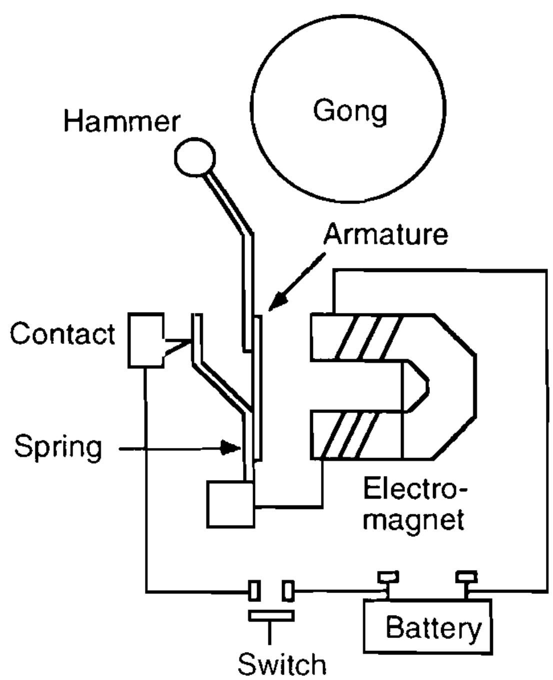

Figure 8. Schematic of a household electric buzzer.

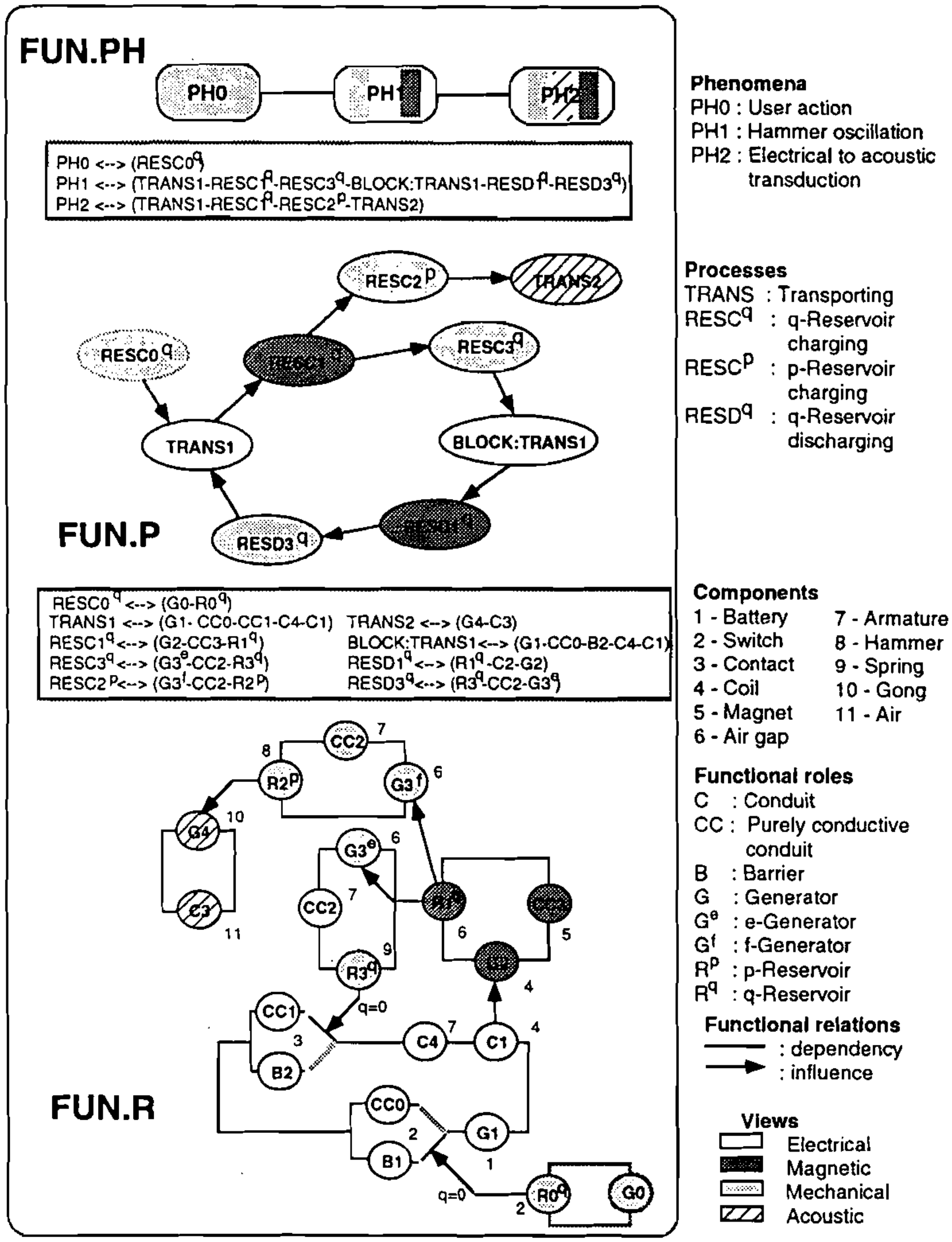

Figure 9. Functional representation of the household electric buzzer.

displacement in the switch. The switch in the electrical view becomes a purely conductive conduit (CCO). This completes the electric circuit through battery (G1), contact (CC1), armature (C4), and the coil (C1) of the electromagnet, enabling an electrical transporting process (TRANS1). When the coil is crossed by current, it acts also as a generator of magnetomotive force (G2), enabling a magnetic circuit through the magnet (CC3) and air gap ($R1^q$). This results in a reservoir charging process ($RESC1^q$) of magnetic flux. The resulting mechanical attraction of the armature is described in terms of both potential ($G3^e$ generates force) and kinetic ($G3^f$ generates velocity) energy. The activation of $G3^f$ enables a reservoir charging process ($RESC2^p$) of momentum in the hammer ($R2^p$), and the hammer striking against the gong (G4) activates an acoustic transporting process (TRANS2). The activation of $G3^e$ enables a reservoir charging process ($RESC3^q$) of displacement in the spring ($R3^q$), and the spring moving apart opens the contact (the corresponding role changes from CC1 to B2), blocking (BLOCK:TRANS1) the existing electrical transporting process.

As a consequence, the coil (C1) is no longer crossed by the current and it no longer acts as a generator of magnetomotive force (G2 becomes a purely conductive conduit), enabling a discharging process of the magnetic flux ($RESD1^q$) that demagnetizes the electromagnet. This, in turn, deactivates $G3^e$ and $G3^f$ and results in a reservoir discharging process ($RESD3^q$) of displacement stored in the spring, rebounding the armature-hammer assembly. When the spring is completely discharged ($q = 0$), it reconnects to the contact (the corresponding role changes from B2 to CC1) and reactivates the electrical transport process (TRANS1).

At the level of phenomena, as long as the switch is held down (PH0), the oscillation of the hammer (PH1) repeats, each time resulting in an electrical to acoustic transduction (PH2).

This example shows how the proposed approach to functional representation allows us to describe the behavior of the system in abstract terms and, at the same time, to keep the description grounded in physics.

INTEGRATION OF STRUCTURE, BEHAVIOR, FUNCTION, AND TELEOLOGY

In this section, we briefly illustrate some basic concepts of our approach to the representation of structure, behavior, and teleology in order to highlight the relations between function and these three types of knowledge.

Integrating Function with Structure and Behavior

In the multimodeling approach the structural model represents the topology of a system using three concepts: (1) components, which represent the physical entities that constitute the system and determine its behavior, (2) nodes, which are used to connect together two or more components, and (3) connections, which describe how components are connected together through appropriate nodes. Components and nodes have typed terminals that are passive channels, supporting possible interaction with the outside environment. Each terminal supports just one kind of physical interaction.

The behavioral model is devoted to represent the potential behavior of the system. It is represented in terms of (1) physical quantities, which are the basic entities used to capture the nature, state, and behavior of a system; (2) physical equations, which represent the relations existing among physical quantities and characterizing the potential behavior of a component or of a node; and (3) operating modes, which provide a characterization of mutually exclusive operating regions of a component.

The link between behavior and structure is realized by associating behavioral primitives to structural primitives, in the sense that each component and node is associated with the physical quantities and equations that describe its behavior in each operating mode.

The link between function and behavior is established through the TOS, in such a way that each physical equation in the behavioral model that is a specialization of a generalized equation in the TOS is associated with the corresponding functional role in the functional role model. Since behavior is related to structure, the association between functional roles and equations results in an indirect assignment of functional roles to structural components. In general, this assignment is many to one: a component is bound to several coexisting functional roles in the same or in different physical domains.

Considering again the example of the door buzzer, Figure 10 shows how the integration of function with structure and behavior is actually accomplished. For simplicity, the figure focuses on a limited portion of the entire device. The structural model (STR) describes which are the components of the system and how they are connected together through nodes. As an example, component CMP4 (the coil) is electrically connected to component CMP1 (the battery) through node N1, and it is magnetically connected to component CMP5 (the magnet) through node N2. The behavioral model (BEH) of the buzzer is made up of a collection of physical quantities and physical equations holding among them. Physical equations are organized according to a set of physical views representing different physical domains. Each component and node in the structural model is associated with the physical quantities and equations that describe its behavior in each operating mode (we illustrate here a single operating mode corresponding to the switch being closed). As an example, component CMP4 (the coil) is associated in the electrical view with Ohm's law (i.e., $V3 - V4 = R1*I3$), and its two terminals (CMP4.ET2 and CMP4.ET1) are associated with electrical currents (I3 and I4) and voltages (V3 and V4). Moreover, CMP4 is also associated in the magnetic view with the equation $M1 = N*I3$, relating the magnetomotive force M1 (associated with the magnetic terminal CMP4.MT1) to the electrical current I3 and the number (N) of turns of the coil. Finally, physical equations are associated with functional roles represented in the functional role model (FUN.R), thus realizing the integration with the functional

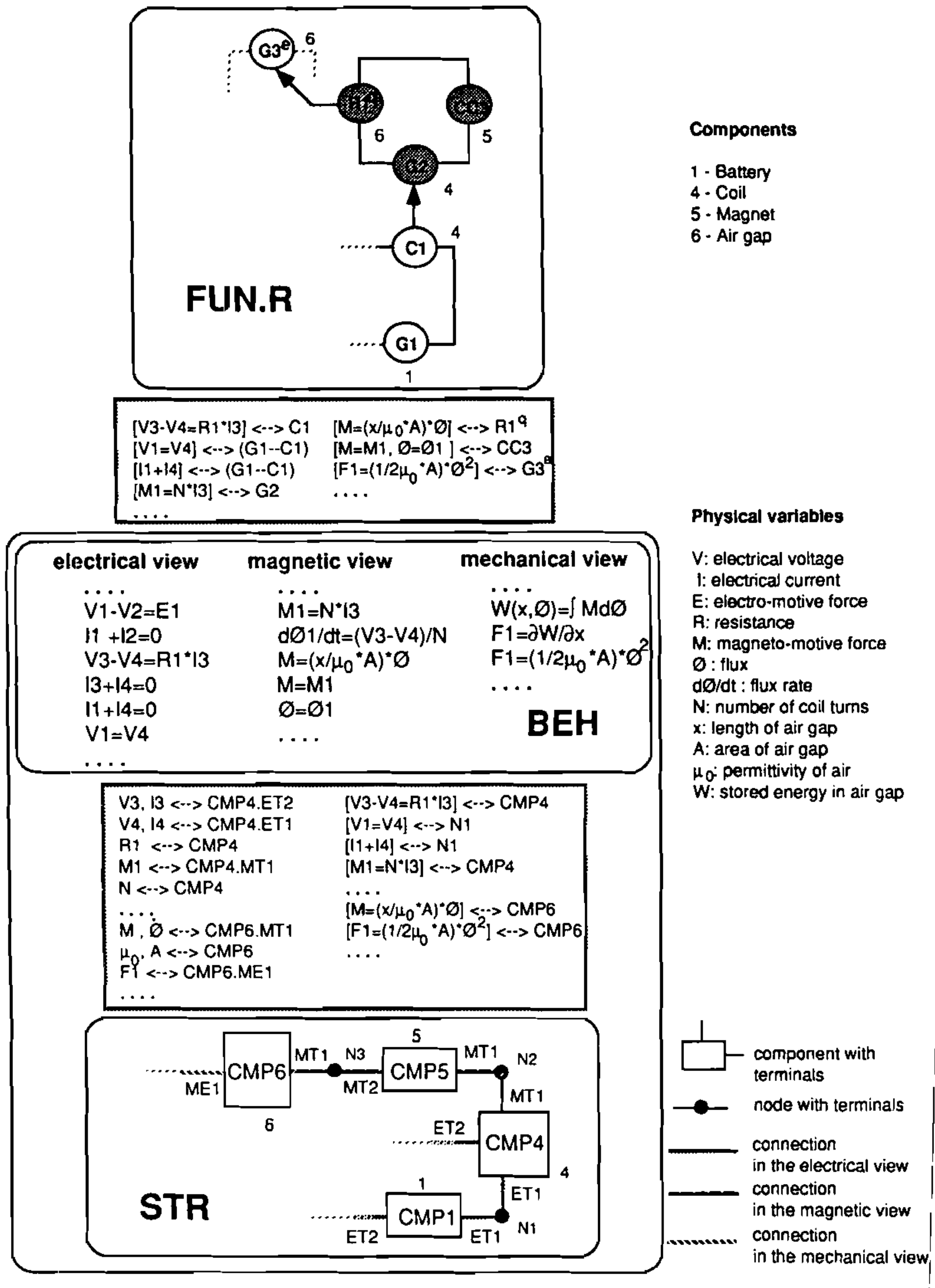

Figure 10. Integration of function with structure and behavior.

representation. For example, Ohm's law V3 – V4 = R1*I3 is associated with a conduit (C1) in the electrical view, while the equation M1 = N*I3 is associated with a generator (G2) in the magnetic view. This results in an indirect assignment of functional roles to components: for example, the coil (CMP4) is both a conduit (C1) in the electrical domain and a generator (G2) in the magnetic domain; the air gap (CMP6) is a reservoir of flux ($R1^{q}$) in the magnetic domain and a generator of force ($G3^{e}$) in the mechanical domain.

Integrating Function and Teleology

The teleology of a system is defined as the specification of the goals assigned to it by the designer. System goals are assumed to be achieved through phenomena. The basic concept in our representation of teleology is the goal. A goal is a triple <goal pattern, operational conditions, intended behavior>, where goal pattern assigns a name to the goal and specifies its arguments, namely typed variables relevant to the definition of the goal (e.g., *to_transfer* x:generalized current *from* y:component *to* z:component; *to_control* x:generalized current *by* y:generalized substance); operational conditions specify the inputs and the setting of controls that should be provided in order to enable the system to achieve the goal; and intended behavior specifies the effects that are expected from the achievement of the goal.

We distinguish among primitive goals and nonprimitive goals. Primitive goals can be directly accomplished by elementary phenomena (e.g., *to_transfer* goals can be achieved by means of elementary phenomena whose organization is constituted by a transporting process). Nonprimitive goals can be achieved by phenomena whose organization is composed of more that one process (e.g., *to_control* goals can be achieved by a phenomenon whose organization is constituted by a reservoir charging process that regulates a transporting process). The teleological model of a system describes the purpose of the system by specifying the goals associated with each part of it. More than one teleological model of a system can be used to represent the teleology associated with the system at different aggregation levels. Each model describes a specific level in the decomposition of a goal into subgoals. Relations between teleological models are represented by subgoal relations which relate goals in a model with the corresponding goals in a finer-grained or coarser-grained model.

The link between function and teleology is thus established through the phenomenon model. This link associates goals with phenomena and is founded on generic engineering knowledge, which denotes "a general arrangement of devices that is well understood" (Bradshaw & Young, 1991) and is used to attain a purpose. In general, this assignment is many to many, that is, a goal can be achieved by several phenomena, or the same phenomenon can participate in the achievement of more than a single goal.

Considering again the example of the door buzzer, Figure 11 shows two teleological models of the device: TEL-0 and TEL-1. Each model describes the

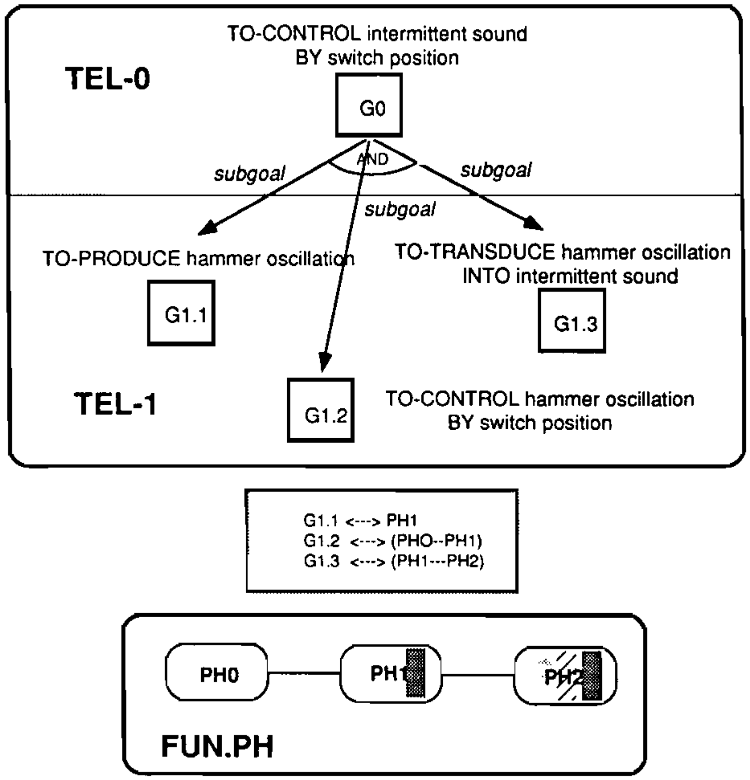

Figure 11. Integration of function with teleology.

purpose of the buzzer at a specific aggregation level. Model TEL-0 represents the goal G0 (i.e., *to_control* intermittent sound *by* switch position) associated by the designer to the door buzzer. Model TEL-1 represents a finer aggregation level, in which the teleology of the device is represented by three goals: goal G1.1 (*to_produce* hammer oscillation), goal G1.2 (*to_control* hammer oscillation *by* switch position), and goal G1.3 (*to_transduce* hammer oscillation *into* intermittent sound). All goals represented are nonprimitive. The figure shows also the link between teleology and function. More specifically, it shows which phenomena described in the FUN-PH model achieve which goals. Note that the same phenomenon PH1 (i.e., hammer oscillation) participates in the achievement of all the goals described in model TEL-1.

APPLICATION TO DIAGNOSTIC REASONING

Research on model-based diagnosis has so far mainly focused on the use of structural and behavioral knowledge, but the resort to functional knowledge is gaining attention in order to increase the efficiency of model-based diagnosis, improve the cognitive coupling with the user of the diagnostic system, and exploit all those observations (e.g., missing processes, presence or absence of generic substances) that the user is able to provide and are more abstract than behavioral.

Chittaro et al. (1993b) focused specifically on the generation of minimal diagnoses of multiple faults based on our functional representation, proposing a functional diagnosis (FD) algorithm. In contrast with more general diagnostic approaches such as the general diagnostic engine (de Kleer & Williams, 1987; Struss & Dressler, 1989), FD is specialized on the peculiarities of the proposed functional representation. This allowed us to exploit the physical knowledge implicit in the representation in order to avoid the need for explicit fault models and the necessity of considering a huge number of combinations of correct models and fault models. This is made possible by three features of the functional model: (1) it is based on generalized functional roles that can undergo only a small set of physically legitimate changes (for example, a conduit cannot become a generator, but it can become a barrier), (2) influences provide an explicit representation of dependence relations between different physical views (for example, a bulb can be a light generator in the optical view only if electrical current flows through it in the electrical view), and (3) processes give a global point of view of the paths followed by generalized flows, and cofunctions of processes identify all functional roles involved in supporting a specific process (in this way, the cofunction ensures that consequences of local role changes are globally reflected).

Implementation of FD does not require to resort to conceptually and computationally complex truth-maintenance machinery such as the Assumption-based Truth Maintenance System. Efficiency benefits also from the possibility of exonerating components from responsibilities when their function is strictly necessary to support observations, thus decreasing the size of conflicts. FD is thus able to efficiently generate all and only the physically possible functional diagnoses.

When a diagnosis cannot be formulated only in functional terms (e.g., slight losses of systems performances, operator errors), the case has to be solved by resorting to other models. This has been experimented with in the Dynamis diagnostic prototype (Chittaro et al., 1989, 1992, 1993a): in contrast to the FD algorithm, which is based on a single type of knowledge, Dynamis allows us to represent symptoms and faults at all levels: structural, behavioral, functional, teleological, and empirical. Dynamis has been implemented in Prolog and tested on examples concerning the diagnosis of several technical systems. The prototype employs a set of diagnostic techniques, such as operator diagnosis (it tries to find an explanation for the symptoms also in potential errors of the operator of the physical system) and diagnosis focusing (it tries to use conclusions reached by a model in order to narrow the part of other models that has to be taken into account for reasoning). Chittaro et al. (1993a) discussed how the functional model can be used in conjunction with other models in order to perform the diagnostic task in a more focused way. It is possible, for example, to start the diagnostic activity at the teleological level to diagnose possible errors made by the operator and/or orient the collection of symptoms using purposes of the system. Then, by exploiting the bridge between teleology and behavior represented by functional knowledge, it is possible to consider the structural and behavioral models in a more focused way. This may result in a considerable refinement of the conflict recognition activity that has to focus only on those parts of the system responsible for the unachieved purposes.

Building an application based on multiple models such as Dynamis requires development of large programs, where control becomes hard to handle and reusability of different models and reasoning utilities is at risk. We thus built a proper software architecture (Chittaro et al., 1992) that supports a modular and easy insertion/retraction of different models and provides facilities for expressing control at various abstract levels (problem, strategy, tactic). We followed the control blackboard paradigm (Hayes-Roth, 1985) because it is especially suited for implementing opportunistic reasoning strategies.

CONCLUSIONS

In this paper, we have illustrated the concept and the representation of function in the multimodeling approach. The main contributions of the presented work are as follows:

- a clear definition of the concept of function that disambiguates function from behavior and teleology
- a physically sound basis for choosing the primitives of the functional representation
- a general and theoretically founded framework for coherently integrating functional models with structural, behavioral, and teleological models

In our current research, we are focusing on the problem of automatically selecting the most appropriate model for a reasoning task and are further studying the application of the multimodeling approach in diagnosis and design, with particular attention to functional reasoning.

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