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Disambiguiation of Qualitative Reasoning with Quantitative Knowledge

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정성추론에서의 모호성제거를 위한 양적지식의 활용

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Abstract

After much research on qualitative reasoning, the problem of ambiguities still hampers the practicality of this important AI tool. In this paper, the sources of ambiguities are examined in depth with a systems engineering point of view and possible directions to disambiguation are suggested. This includes some modeling strategies and an architecture of temporal inference for building unambiguous qualitative models of practical complexity. It is argued that knowledge of multiple levels in abstraction hierarchy must be reflected in the modeling to resolve ambiguities by introducing the designer's decisions. The inference engine must be able to integrate two different types of temporal knowledge representation to determine the partial ordering of future events. As an independent quantity management system that supports the suggested modeling approach, LIQUIDS(Linear Quantity-Information Deriving System) is described. The inference scheme can be conjoined with ordinary rule-based reasoning systems and hence generalized into many different domains.

1. Introduction

Qualitative modeling research is expected to provide the basic technology for model-based deep reasoning of system dynamics, which is required for intelligent monitoring, diagnosis, and compensation of complex systems. Qualitative models are robust, can be decomposed and aggregated, and use as little knowledge as necessary to predict behavior of target systems. In comparison with conventional numeric models, the inference and knowledge structure of qualitative models are closer to those of human experts and hence more explicatory.

Perhaps the most conspicuous weakness of qualitative reasoning is the problem of seemingly unavoidable ambiguities. As the target system gets larger and more complicated, am-

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biguity tends to grow up and finally degrades the predictive power of the model to make its use for serious applications impractical.

A source of ambiguities in qualitative reasoning is its parsimonious use of information on the behavior of the target systems, which is one of its strong points. That is, the only information qualitative reasoning uses and produces is what is related to meaningful changes of the system state. Other arbitrary questions are left unquestioned and unanswered.

Besides the above reason that appears to be inherent to qualitative reasoning, deKleer[2] pointed out that ambiguities can also originate from insufficient information for temporal ordering. The third source of ambiguities is the limitation of qualitative models' knowledge representation.

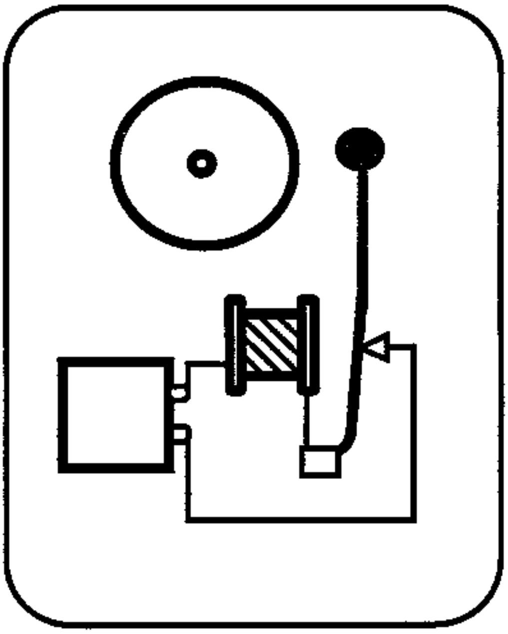
In the following sections, these sources of ambiguities will be examined in more depth with a systems engineering point of view and possible directions to disambiguation will be suggested.

2. Ambiguities and Functional Abstraction

As mentioned above, a type of ambiguity is closely related with the parsimonious use of information by qualitative models, which is why they are preferred to numeric models. When the system state is qualitatively represented, fine-grained distinctions will not be available between the attribute values or system states. The presense of such ambiguities is indeed a nature of qualitative models, but they are not uncontrollable by the modeler. This is best illustrated by an example.

Figure 1 shows the structure of a simple doorbell. The causalities for its operation are diagrammed in Figure 2. When the clapper is at its rest position, the circuit is closed and the current will flow. Then a magnetic field developed by the coil will pull the clapper to let it hit the bell. Meanwhile, since the clapper's movement opened the circuit, the current and magnetic field have been disappeared. The clapper, having some restoring force in itself, then comes back to its original position only to start an identical next cycle. An ambiguity is exposed when a question is asked whether the magnetic force is stong enough to overcome the restoring force of clapper. If it is not, the clapper will never be lifted and the subsequent events will be aborted. Another question is if the accelaration of the clapper by the magnetic force is strong enough to make it to reach at the bell rather than returning back in the middle.

The original sequence of events was a simple but legitimate explanation of the working of a doorbell. People rarely ask the above questions since the 'right' answers are obvious if the doorbell is to achieve its purpose. A finer-grained set of causalities would be concerned with the possible digression from the original intention of doorbell and would require some information on the relative strengths of forces. In a model described at a rather abstract level, it may be enough to have a statement that the clapper's hitting of the bell comes earlier than its turning back to the rest position. As thedescription becomes more physical, however,



[Figure 1] A Simple Doorbell

the model must reason in terms of such parameters as the force of field, the restoring force, and even the time length during which accelaration by the field continues.

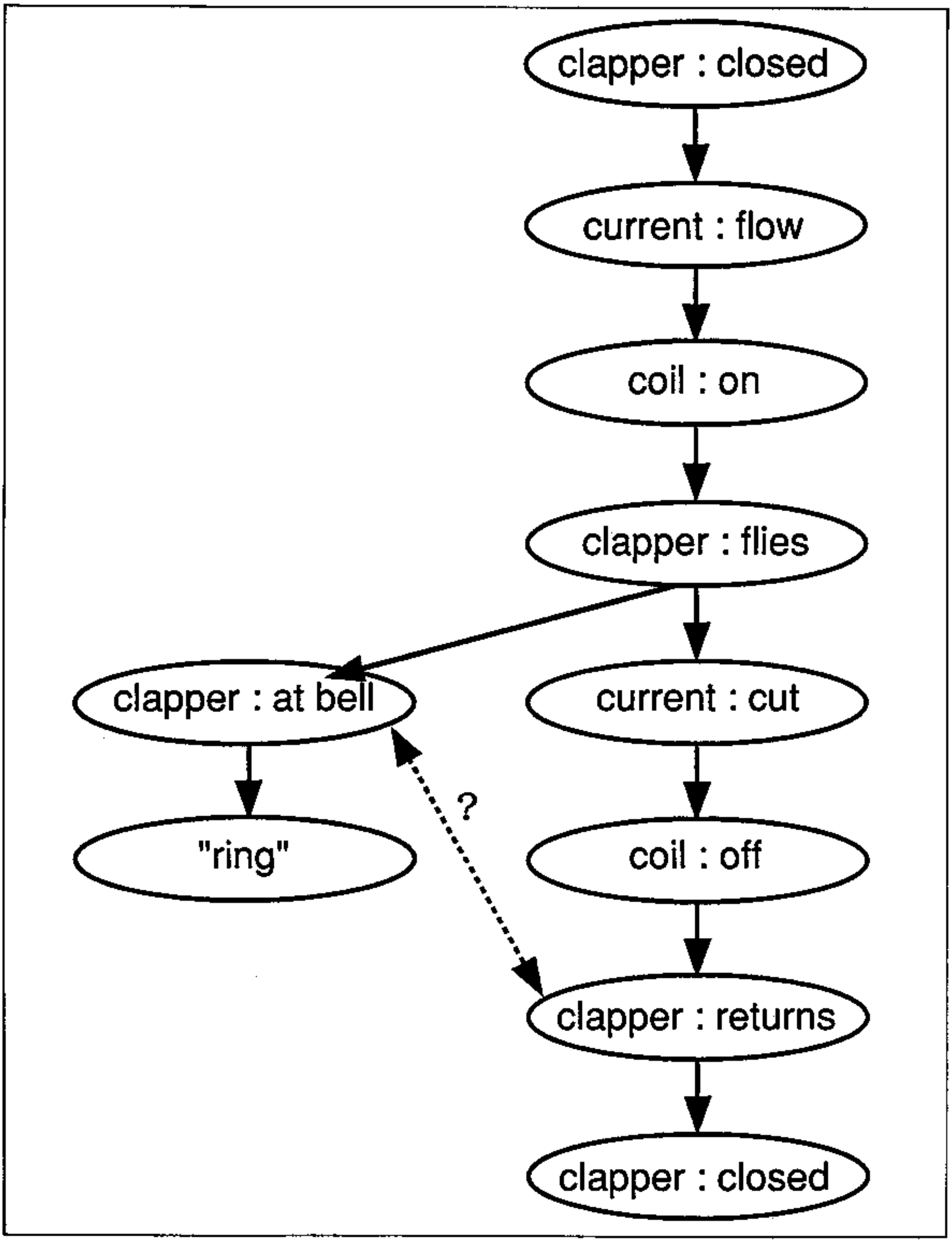
As the above example illustrated, a qualitative model can be described at different levels of abstraction. Rasmussen[7] described the abstraction hierarchy as shown in Figure 3. The intention of a system has stronger implication at a higher abstraction level while the description gets more analytical at a lower abstraction level. The highest abstraction is the purpose of a system. Then follow the level of abstract function, generalized functions, physical functions, and finally, physical form. The engineer would normally design a system starting from the functional purpose, the highest level, and continue with successively lower abstaction levels. When a description of system behavior is translated to a description of the next lower abstraction level, things need to be quantified. In the above example, where the designer must design the bell to ring, he/she will try to ensure that the clapper hits the bell before it turns back. This specification then will be realized adjusting the magnetic force and the restoring force.

In general, ambiguities occur when a question is asked at a lower level of abstraction than the level at which the model is stated. The higher level model involves more assumptions based on the intention, and the lower level model that has more degree of freedom must be constrained to achieve the higher level prescription. This constraining is primarily done by appropriate arrangement of quantitative parameters.

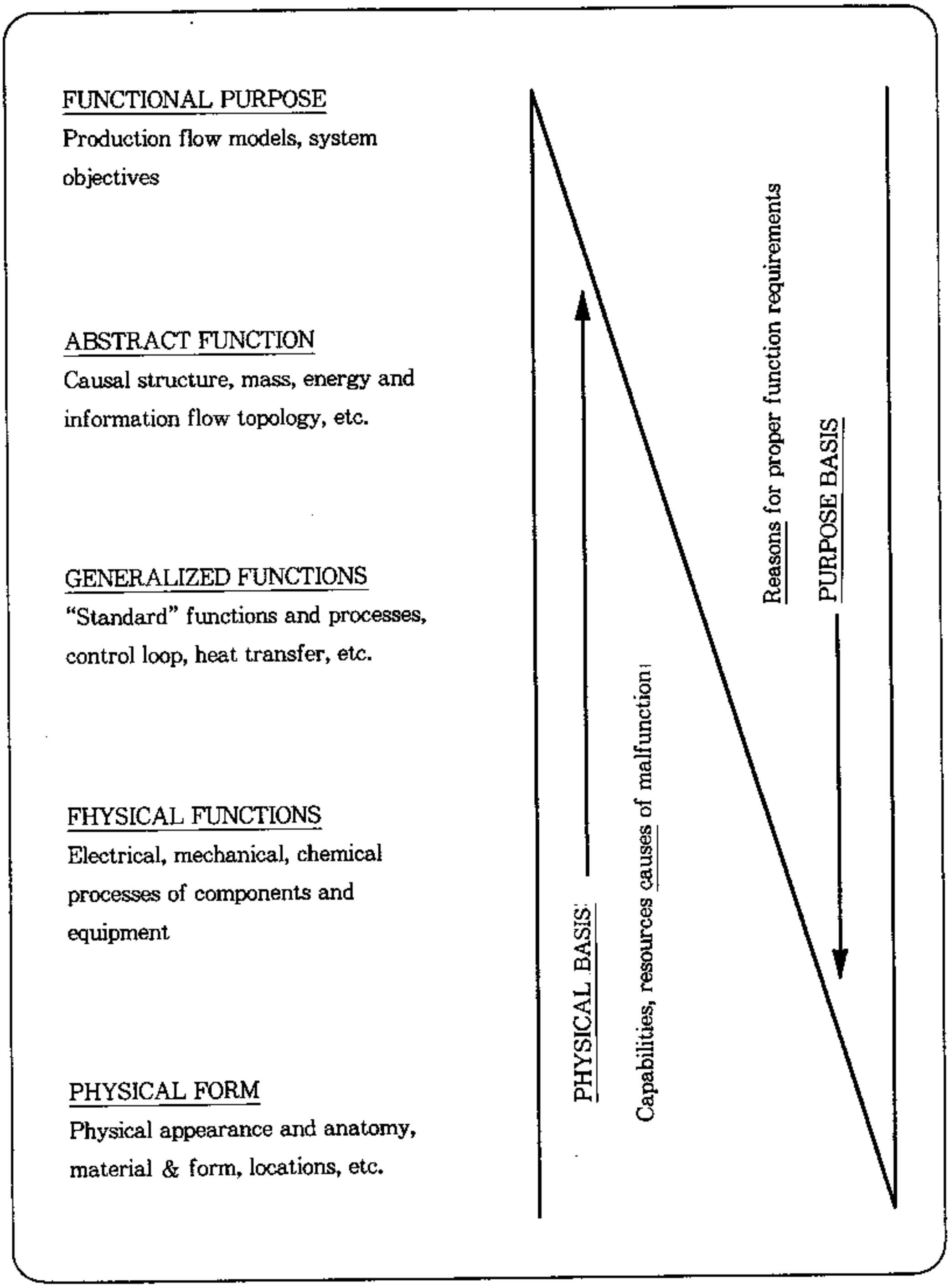
For proper disambiguation, the model should be built at an abstraction level that is low enough to have the required freedom of deviating behavior. On the other hand, taking unnecessarily low abstraction level may lead to a model that is too large, laborious to build, fragile, and inefficient. What is then the right level of abstraction for a model? To answer this, the model builder should take the purpose and context of the use of the model into account and undertake systems analysis which is not much different from anaysis stage for software development.

3. Temporal Ambiguities

In qualitative models, time is represented as a sequence of time segments. Nothing but the



[Figure 2] A Sequence of Events



[Figure 3] Abstraction Hierarchy (Rasmussen 1985) order of events is captured in the reasoning and the lengths of intervals are either ignored or implicitly considered only for determining the order of events. Normally, any significant time point must be determined on the time axis to have precedence relationship to all other meaningful time points. This seems inevitable as long as the model attempts to represent the system's behavior as a sequence of system states, a strategy related to situation calculus.

As some researchers argued[4, 9], this idea of completely ordered sequence of time points imposes great limitations on the qualitative reasoning about complex dynamic systems. The reason is that such models cannot tolerate temporal ambiguities that are prevalent and often harmless in human reasoning. More desirable models would be those that have the ability to predict future events that are partially ordered yet unambiguous enough to answer the meaningful questions. It is crucial, therefore, to be selective between the significant precedence relationships and insignificant ones.

The pairs of events that need to be temporally interrelated depend on what information the dynamics of the target system requires. The necessary relationships appear in the form of triggering and intervening conditions in causation rules. These conditions must be examinable with the knowledge that the model is given or brings forth by its inference. Thus the first principle of temporal disambiguation is to have the model's dynamics stated in a coherent manner so that the model produces temporal information in the form it can use later. An important necessary condition of such coherence is that the system dynamics must be stated at the right levels of abstraction.

The time point of an event can be appointed in two different ways: one is crossing of thresholds by moving variables and the other is explicit quantification of the time lengths of states. Temporal knowledge that comes from quantitative processes can mainly be represented in the former while temporal knowledge about purely qualitative processes should be described in the latter. The model's knowledge representation must allow those two fashions of description and the inference engine must be able to integrate both to determine future event ordering. To this end, Yoon[10] claimed that explicit designating and handling of time interval lengths is mandatory.

Many system dynamics that qualitative models try to describe are cyclic as a whole or in part. This dictates that accumulation of time intervals must be operationally possible during termporal inference, while the line of temporal reasoning schemes originated from Allen's work [1] comes closest to this capability, the resolution of temporal knowledge is not enough for giving unambiguous result after a long chaining. Also, to prevent the model from cycling and overflowed by the accumulated time intervals, the renewal of same behavior should be noticed.

To meet the second and third conditions for proper disambiguation, it is clear that the time intervals should be manipulated more explicitly than most of current models. The description of time relationships must be as expressive as that of ordinary quantities.

4. Limitations of the Model's Knowledge Representation

If a model's insufficient expressive power is to be blamed for ambiguous reasoning, the knowledge limited by the representation scheme is most likely that about quantities. As we discussed above, quantification of physical parameters is the designer's primary means to resolve ambiguities and meet the intentions of systems. Therefore, any unambiguous description of system dynamics tends to contain a lot of quantitative information and tests. It follows that unambigous reasoning is possible only when a general and flexible handling of quantity information is provided. Ideally, except being qualitative, no further information loss should arise due to the model's particular scheme of quantitative knowledge representation.

Such a powerful processing of quantity information cannot be expected if the processing is embedded in the inference on the system dynamics. Although the quantitative information is encoded and handled in qualitative ways by a qualitative model, it certainly preserves the nature of quantities. For example, if a quantity is changing, it is either increasing or decreasing. Therefore, exactly as the number system is independent of any physics laws, a quantity information management system that is independent of model's dynamics is conceivable. Since the inference on the behavior of quantities can be much more powerful than general symbolic inference owing to the inherent characteristics and rules of the quantity system, having an independent quantity-reasoning system, such as LIQUIDS described in the next section, is certainly desirable.

5. LIQUIDS(Linear Quantity Information Deriving System)

The concept of quantity space is developed to manage quantity information in qualitative ways. The term 'qualitative' is used to contrast this apporach with numeric representation and processing of quantity information. In a quantity space, the quantities are valued by ordinal relationships among themselves or numbers.

An explicit algorithmic presentation of a quantity space management system was given by Simmons[8]. More well-known approaches to qualitative simulation including those of Kuipers[6], deKleer[3], and Forbus[5] usually embedded the quantity information management in the inference of the system dynamics. Simmons' quantity space management system, named Quantity Lattice, combines inequality reasoning with reasoning about simple arithmetic expressions such as addition or multiplication. The inference emphasizes computational efficiency and is not general enough even for linear relationships among several variables.

LIQUIDS(LInear QUantity Informtion Deriving System) is a quantity space management system that can handle any complicated linear expressions. Its inference is centered around linear programming techniques and fairly efficient. In a qualitative model which is primarily to simulate the human ability of robust prediction of system behavior, such a general algorithm is much more desirable than an arbitrarily constrained algorithm. Another motivation for LIQUIDS is that, except very simple multiplication and division, most of our commonsense quantitative inference appears to be linear as examplified by frequent accumulation of amounts or time intervals.

Time is a very special type of quantity in LIQUIDS that it is represented in two different ways. Explicit time lengths are handled as ordinary quantities in their own quantity subspace. In the other way, time presents itself implicitly through integration/differentiation of quantities. At every time intervals and time points, the knowledge in a quantity subspace is changed according to quantity subspaces of immediately lower and higher orders. Note that a differentiation is achieved by qualitative version of mean theorem and hence calls for nonmonotonous reasoning along the time axis. Integration is more straightforward than differentiation and executed whenever time advances by searching non-zero derivatives and consecutively recompose the inequalities in the quantity subspaces of higher orders accordingly. LIQUIDS depends on forward chaining in propagation of time effects, but on backward inference elsewhere,

The key for the effeciency of LIQUIDS is its selective operation of which attention is narrowed by a given set of quantity conditions which trigger meaningful changes in the target systems. For example, if there is no testing of the lowerbound of a quantity X(e.g., $X>Y+Z$) for triggering a rule in the rule base, the changes of inequalities that might be caused by X's increasing is excluded from consideration in finding the next event. Such changes are taken into account only when a non-triggering quantity condition is queried to the quantity space.

With the support of LIQUIDS, the builder of a qualitative model is benefitted in two ways. First, the versatility of quantity information that is manipulatable in LIQUIDS will expand the modeler's freedom of expression in compiling the knowledge of dynamics. Second, the modeler can be more concentrated on the issue of good modeling practice discussed through this paper. LIQUIDS was developed in Allegro CommonLisp on a Macintosh II computer.

6. Concluding Remark

The research presented in this paper was pursued both conceptually and experimentally. Qualitative models, despite their prospective characteristics, have not been used in practical situations. The dilemma the researchers in this area faced was the conflict between to build a good theoretical foundation and to develop a practically useful technology. What is wanted now is a set of good disciplines of qualitative modeling to make it practical and yet to prevent it from becoming ad-hoc programming technique. This paper attempted to apply a systems engineeering point of view to derive those modeling disciplines.

The temporal inference engine and LIQUIDS were experimentally constructed and tested with examples. The future research effort will be refining those to build a complete system that may well be called a ***dynamic expert system***.

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