10. Knowledge Organization and Its Role in Temporal and Causal Signal Understanding: The ALVEN and CAA Projects

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Abstract

This paper describes the ALVEN and CAA projects. These projects share many basic concepts particularly with respect to the representation of knowledge and to the hypothesize and test nature of the control strategy. They both deal with temporally rich data interpretation tasks. However, they focus on very different aspects of interpretation. ALVEN processes images of a time-varying sequence in a real-time fashion (although not in real time), while CAA considers an entire signal, as if time were a second spatial dimension. ALVEN deals with the assessment of the performance of the human left ventricle from an X-ray image sequence, while CAA considers the causal relationships of the electrophysiology of the human heart and the resulting electrocardiogram signal, and tries to detect and classify anomalies of rhythm. The contributions of these works lie in the elucidation of a representation and control structure for the knowledge-based interpretation of time-varying signals.

Based on the paper, Building Knowledge-Based Systems, J. Mylopoulos, T. Shibahara, and J. Tsotsos, appearing in COMPUTER, Volume 16, Number 10, October, 1983.

10.1. Introduction

The development of the ALVEN and CAA systems represents a long-term research effort over the past ten years. The basic approach involves exploiting frame-based representations for interpretation. Frames are organized into a semantic network, and a control strategy has been developed that is driven by those organizational axes. ALVEN uses the generalization/specialization, aggregation/decomposition, similarity and temporal axes, while CAA adds a causal dimension to this set. The remainder of this paper will discuss several aspects of the two systems, with the bulk of the discussion devoted to the CAA system. Details on ALVEN have appeared in several previous publications (Tsotsos, 1984), (Tsotsos, 1985). All of the examples presented in section 10.2 are from the ALVEN system, and examples from the CAA system all appear in section 10.5. The discussions in sections 10.2 and 10.3 summarize features that the two systems have in common.

10.2. The representational scheme

10.2.1. Knowledge packages: classes

Packaging up knowledge leads to a modular representation, with all the advantages of modularity, particularly the enhancement of clarity and flexibility. Most knowledge package representation schemes borrow strongly from (Minsky, 1975). Our frames are called classes and borrow much from the Procedural Semantic Networks formalism (PSN) of (Levesque and Mylopoulos, 1979). A class provides a generalized definition of the components, attributes and relationships that must be confirmed of a particular concept under consideration in order to be able to make the deduction that the particular concept is an instance of the prototypical concept. Classes also have embedded, declarative control information, namely exceptions and similarity links. These features will be described shortly. Note that there is a distinction between the "prerequisites" of the class (those components that must be observed in order to instantiate the class) and the "dependents" of a class (those components that must be derived on instantiation). Dependent slots carry their own computation information. Classes exhibit large grain size, and translating their contents to rules would require many rules. An obvious advantage over the rule scheme is that elements that conceptually belong together are packaged together into a class, with some control information included. Other frame-based schemes for medical consultation systems include the MDX system (Chandrasekaran et al, 1979) and CADUCEUS (Pople, 1982).

10.2.2. Knowledge organization

When confronted with a large, complex task, "divide and conquer" is an obvious tactic. Task partitioning is crucial; however, arbitrary task sub-division will yield structures that are unwieldy, unnecessarily complex or inappropriately simple. Furthermore they have poorly defined semantics, lead to inefficient processing, and lack clarity and perspicuity. Within the existing representational repertoire, there exist two common tools for domain sub-division and organization, namely the IS-A relationship (or generalization/ specialization axis), and the PART-OF relationship (or the part/whole axis or aggregation/decomposition). (Brachman, 1979), (Levesque and Mylopoulos, 1979), (Brachman, 1982) provide discussions of their properties, semantics and use. The IS-A, or generalization/ specialization relationship, is included in order to control the level of specificity of concepts represented. IS-A provides for economy of representation by representing constraints only once, enforcing strict inheritance of constraints and structural components. It is a natural organizational scheme, and provides a partial ordering of knowledge concepts that is convenient for top-down search strategies. In conjunction with another representational construct, SIMILARITY, IS-A siblings may be implicitly partitioned into discriminatory sets. The PART-OF or aggregation relationship allows control of the level of resolution represented in knowledge packages and thus the knowledge granularity of the knowledge base. It provides for the implementation of a divide-and-conquer representational strategy, and it forms a partial ordering of knowledge concepts that is useful for both top-down and bottom-up search strategies. Concept structure can be represented using slots in a class definition. The slots form an implicit PART-OF relationship with the concept. Representational prototypes (classes) are distinguished from and related to tokens by the INSTANCE-OF relationship. Instances must reflect the structure of the class they are related to; however, partial instances are permitted in association with a set of exception instances, or the exception record, for that class. In addition, a third type of incomplete instance is permitted, namely the potential instance or hypothesis. This is basically a structure that conforms to the "skeleton" of the generic class, but that may have only a subset of slots filled, and has not achieved a certainty high enough to cause it to be an instance or partial instance. Details on the precise semantics of IS-A, PART-OF and INSTANCE-OF may be found in (Levesque and Mylopoulos, 1979).

10.2.3. Multi-dimensional levels of detail

The term "level of detail" seems to denote different things to different people. In most schemes, it is used to express problem decomposition only (Nilsson, 1971). We present two separate views of abstraction "level". These views are related to the fact that all concepts have both IS-A and PART-OF relationships with other concepts. Thus, the level of specificity of detail can be controlled by, or examined by traversing, the IS-A hierarchy, while the level of resolution of detail (decomposition in other schemes) is reflected in the PART-OF hierarchy. In (Patil et al, 1982), only the decomposition view of level is present, while in CADUCEUS, (Pople, 1982), it seems that the level of specificity is employed and level of resolution is restricted to causal connections. In (Wallis and Shortliffe, 1982) rule complexity is used, which may be likened to our view of level of resolution; however, its use is restricted to explanation.

10.2.4. Time

Several interacting mechanisms are available for the representation of temporal information. This multi-pronged approach differs from other schemes that embody a single type of construct for handling temporal information. The complexity of time necessitates several special mechanisms. Our approach differs from others (Allen, 1981), (Mead and Conway, 1980), in that we have been motivated by problems in signal analysis rather than in representing natural language temporal descriptions and their inherent ambiguity and vagueness. It is not clear, for example, what kind of control strategy can be employed along with Allen's scheme of temporal representation. Fagan (Fagan, 1980) is concerned with a temporal interpretation situation. However, there are a number of issues, primarily in control, that are not considered by his system, VM:

- using the rule-based approach, only a data-driven recognition scheme is incorporated, and thus, VM cannot instigate a search for temporally expected events;

- the handling of noise is not formalized, but is rather ad hoc;

- the complexity of temporal relationships among rules seems limited, and arbitrary groupings of temporal events and their recognition are not addressed;

- expectations in time are table-driven, and no distinction is made between them and default values or expected ranges. Expectations in ALVEN are computed from such information, but current context is taken into account as well, so that expectations are tailored for the task at hand;

- partial satisfiability of temporal event groupings cannot be handled.

In addition, Long and Russ also address the problem of time-dependent reasoning (Long and Russ, 1983). Their scheme is closer to Fagan's than to ours. The control is data-driven exclusively; we have already highlighted the deficiencies of this approach as a general reasoning scheme. Their representation of time, however, shares some similarities with ours in that both points and intervals are used, and special meaning is assigned to the variable "now".

A brief description of the representation of time used by ALVEN follows. A TIME_INTERVAL class is defined that contains three slots, namely, start time, end time and duration. This class can then be included in the structure of any other class and would define its temporal boundaries and uncertainty in those values. Using those slots, the relations before, after, during, etc., (similar to (Allen, 1981)) are provided. In constraint or default definition, sequences of values (or ranges of values) may be specified using an "at" operator, so that in effect a piecewise linear approximation to a time-varying function can be included. In this case, of course, constraint evaluation must occur at the proper point in time. Tokens of values such as volume or velocity for which use of this operator is appropriate, have two slots, one for the actual value and the other for the time instant at which that value is true. The time instant slot is a dependent slot whose value is set to the value of the special variable "now" (current time slice). Note that this kind of mechanism could easily be expanded if required to multi-dimensional functions.

Finally, arbitrary groupings of events can be represented. The set construct (which may be used for any type of class grouping, not only for events), specifies elements of a group, names the group as a slot, and has element selection criteria represented as constraints on the slot. (Patil et al, 1982) describe a version of temporal aggregation similar to ours, but do not seem to have a time-line along which selection of values can occur, nor do they distinguish between aggregations of events and sequences of measurements.

Since knowledge classes are organized using the IS-A and PART-OF relations, their temporality is as well. By constructing a PART-OF hierarchy of events, one implicitly changes the temporal resolution of knowledge classes (as long as simultaneous events are not the only ones considered). For example, suppose that the most primitive events occur with durations on the order of seconds. Then groupings of those may define events that occur with durations in the minute range, and then groupings of those again on the order of hours, and so on. Events whose durations are measured using months can be so built up. Yet, many kinds of events cannot be so decomposed, and there is no requirement that all events have such a complete decomposition. Those events however, are not left hanging, since they will also be related to others in the knowledge base via the IS-A relationship. The control scheme makes use of the temporal resolution with respect to sampling rates and convergence of certainties.

In the following examples, first the TIME_INTERVAL class is shown, followed by the class for the concept of SEQUENCE, followed by a constraint on volume of the left ventricle from the normal left ventricle class, showing the use of the "at" mechanism for both default and constraint definition.

example 1

```
class TIME_INTERVAL with
prerequisites
   st : TIME_V such that [st >= 0];
   et : TIME_V such that [et >= st];
dependents
   dur : TIME_V with dur ← et - st;
end $
```

example 2

```
class SEQUENCE is-a MOTION with
prerequisites
   motion_set : set of MOTION such that [
       for all m : (MOTION such that
             [m element-of motion_set])
           verify [
             m.subj = self.subj,
             ~find m1 : MOTION where [
             m1 element-of motion_set,
             (m1.time_int.st during m.time_int or
             m.time_int.st during m1.time_int) ],
```

```
            find m2 : MOTION where [
               m2 element-of motion_set,
               (m.time_int.st = m2.time_int.et or
               m2.time_int.st = m.time_int.et ) ] ] ,
            card(motion_set) > 1,
            strict_order_set(motion_set,time_int.st) ] ;

dependents
   first_mot : MOTION with
       first_mot ← earliest_st(motion_set) ;
   last_mot : MOTION with
       last_mot ← latest_st(motion_set ;
   time_int : with time_int ←
       ( st of TIME_INTERVAL with st ←
     first_mot.time_int.st ,
      et of TIME_INTERVAL with et ← last_mot.time_et );

end $
```

example 3

```
volume : VOLUME_V with
    volume ← (vol of VOLUME_V with
      vol ← (minaxis.length  now ) ** 3
        default(117  m.systole.time_int.st,
                 22  m.systole.time_int.et,
                 83  m.diastole.rapid_fill.time_int.et,
                100  m.diastole.diastasis.time_int.et,
                117  m.diastole.atrial_fill.time_int.et)
        such that [
      volume  m.diastole.time_int.et >= 97
        exception [TOO_LOW_EDV with volume ← volume ],
      volume  m.diastole.time_int.et <= 140
        exception [TOO_HIGH_EDV with volume ← volume ],
      volume  m.systole.time_int.et >= 20
        exception [TOO_LOW_ESV with volume ← volume],
      volume  m.systole.time_int.et <= 27
        exception [TOO_HIGH_ESV with volume ← volume] ] ,
    time_inst of VOLUME_V with time_inst ← now ) ;
```

10.2.5. Exceptions and similarity relations

The recording of exceptions to slot filling and constraint matching has proven to be valuable. Exceptions are classes in their own right, with slots to be filled on instantiation, that is, when raised. Each slot constraint (or group of constraints) of a class may have an associated exception clause. This clause names the type of exception that would be raised on matching failure, and provides a definition for filling the exception's slots, since these slot fillers identify the context within which the exception occurred and play an important role in the determination of the action to take on the exception. Each slot has an implicit exception associated with it for cases where a slot filler cannot be found. Exceptions are used in two ways: 1) to record the matching failures of current hypotheses, recording the failures of the reasoning process; and 2) to assist in directing system attention to other, perhaps more viable, hypotheses. The prototypical exception class is shown below along with one of its specializations, followed by an example from a stroke volume slot. Other examples have already appeared.

example 1

```
class EXCEPTION with
dependents
   subj : PHYS_OBJ ;
   time_int : TIME_INTERVAL ;
   source_type : CLASS ;
   source_id : INTEGER ;
end $
```

example 2

```
class TOO_MUCH_MOTION is-a EXCEPTION with
dependents
   seg : STRING ;
   disp : LENGTH_VAL with disp ←
            (len of LENGTH_VAL with
        len ← dist(subj.centroid @ source_id.time_int.st,
                   subj.centroid  source_id.time_int.et ) ,
        time_inst of LENGTH_VAL with time_inst ← now) ;
end $
```

example 3

```
stroke_vol : VOLUME_V with
        stroke_vol ← (vol of VOLUME_V with
          vol ← self.volume  m.diastole.time_int.et -
                             self.volume
    @ m.systole.time_int.et
                default(95) such that [
```

```
            vol >= 70
               exception [LOW_STROKE_VOLUME with
                  volume ← vol ],
            vol <= 120
               exception [HIGH_STROKE_VOLUME with
                  volume ← vol ] ],
     time_inst of VOLUME_V with time_inst ← now) ;
```

Similarity measures that can be used to assist in the selection of other relevant hypotheses on hypothesis matching failure are useful in the control of growth of the hypothesis space. These measures usually relate classes that together comprise a discriminatory set, that is, only one of them can be instantiated at any one time. As such, they relate classes that are at the same level of specificity of the IS-A hierarchy, and that have the same IS-A parent classes. Similarity links are components of the frame scheme of (Minsky, 1975), and a realization of SIMILARITY links as an exception-handling mechanism is presented in (Tsotsos et al, 1980) based on a representation of the common and differing portions between two classes. This view is contrasted with the sets of competitors described for the ABEL system (Patil et al, 1982). In that formulation, the level of specificity of the competing set is not represented. Similarity links enable explicit discussion of class comparisons, not only between the connected classes, but also by traversals of several links (Gershon, 1982). Thus, they are an element of embedded declarative control, and add a different view of class representation, thereby enhancing redundancy of the representation. The three major components of a SIMILARITY link are the list of target classes (given first), the "similarities" expression,[29] and finally the "differences" expression, the time-course of exceptions that would be raised through inter-slot constraints of the source

[29] A similarities expression indicates the important common portions between the source and target classes - during interpretation, the target classes are not active when the SIMILARITY link is being evaluated. Thus, in time-dependent reasoning situations, the components of the target class that are the same as in the source class before activation of the SIMILARITY link, or that the source class may not care about that have already 'passed in time', can be verified using the similarities expression.

class or in parts of the source class. There is an implicit conjunction of the differences in the exception record, while the similarities form a disjunction. Many SIMILARITY links will be shown in subsequent examples.

10.2.6. Partial results and levels of description

Partial instances are permitted with an accompanying exception record. More importantly, since instance tokens are produced for each verified hypothesis, and since hypotheses maintain the organization exhibited by the classes that they are formed from, interpretation results also exhibit the same structure. That is, there are levels of description that may examined as appropriate by a user.

It is important to realize that the instantiation of a hypothesis is achieved only when its certainty has reached a threshold value. (The thresholds are not set in an ad hoc fashion, but rather depend on a number of factors relating to the context of interpretation and knowledge structure - see (Tsotsos, 1984) for details). Thus, even though not all components of a hypothesis have been verified, instantiation may still take place if that hypothesis has significantly more successes than its competitors over the same time period. This would then create a partial instance, including the verified components, the final certainty, and a set of exception records specifying what was not observed.

10.3. The interpretation control structure

ALVEN and CAA employ hypothesize-and-test as the basic recognition paradigm. The activation of a hypothesis sets up an internal goal that the class from which the hypothesis was formed tries to verify itself. However, activation of hypotheses proceeds along each of five dimensions concurrently, and hypotheses are considered in parallel rather than sequentially. These dimensions are the same class organization axes that are described above. Specifically, we define: **goal-directed** search to be movement from general to specialized classes along the IS-A dimension, the goal being to find the appropriate sub-class definition for the data in question; **model-directed** search to be movement from aggregate to component classes along the PART-OF dimension; **temporal** search to be a specific form of model-directed search in that a temporal ordering among components controls the time of activation; **failure-directed** search to be movement along the SIMILARITY dimension; and **data-directed** search to be movement from components to aggregates of components upwards along the PART-OF dimension. For a given set of input data, in a single time slice, activation is terminated when none of the activation mechanisms can identify an un-activated viable hypothesis. Termination is guaranteed by virtue of the finite size of the knowledge and the explicit prevention of re-activation of already active hypotheses. The activation of one hypothesis has implications for other hypotheses as well, as will be described below. Because of the multi-dimensional nature of hypothesis activation, the "focus" of the system also exhibits levels of attention. That is, in its examination, the focus can be stated according to desired level of specificity or resolution (the two are related), discrimination set, or temporal slice. The control structure is illustrated in Figure 10-1.

Each newly activated hypothesis is recorded in a structure that is similar to the class whose instance it has hypothesized. This structure includes the class slots awaiting fillers, the relationships that the hypothesis has with other hypotheses, and an initial certainty value determined by sharing the certainty with the hypothesis that activates the new hypothesis.

In other aspects, the systems differ and these differences are highlighted in upcoming sections of this paper.

10.4. The ALVEN project

10.4.1. Overview

The ALVEN project was an experiment in the design of a framework for the integration of time into high level (attentive) vision. The key elements are an organization of knowledge along several axes, including time; several search modes facilitated by the knowledge organization; a hypothesize-

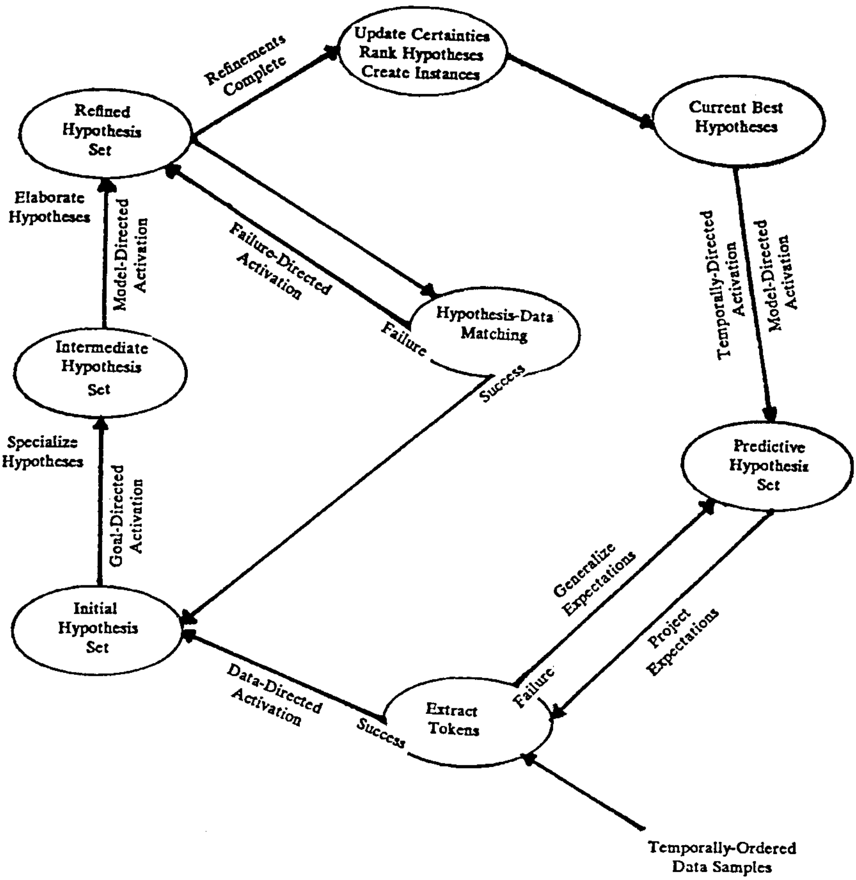

Figure 10-1: The Interpretation Control Structure.

and-test reasoning framework; and a temporal cooperative process, driven by the knowledge organization, for hypothesis ranking. The major aspects of the cooperative process, namely, the definition of consistency, process neighbourhoods, initial certainties, compatibility factors, are all defined in terms of the knowledge organization. Iterations are tied to temporal measurements, and this allows temporal sampling to be discussed quantitatively. A qualitative analysis that includes hypothesis response rise and fall times is presented in addition to guidelines for setting compatibilities such that performance is appropriate. The scheme subsumes previous relaxation methods in that iterations are performed in time for either dynamic or static situations, and because the structure over which the cooperative process operates is allowed to change with time. It is further shown that the dimensions of knowledge organization, IS-A, PART-OF, SIMILARITY and Temporal Precedence, have uses far beyond their desirable structuring and access properties, and that they play important other roles in a knowledge based interpretation scheme. The application domain was chosen because of its rich temporal nature.

The evaluation of left ventricular (LV) performance by computer from cine representations of LV dynamics is a difficult and long-studied problem. A large number of heuristics have been proposed for measuring shape changes (Brower and Meester, 1981), following anatomical landmarks (Slager, 1979), computing segmental volume contributions (for a comparison, see (Gerbrands et al, 1979)), etc., all performing with varying degrees of success, but being applied independently of each other. Although such heuristics are indeed valuable quantitative measures, we propose that their limited performance is due to two key considerations: 1) it is unlikely, given the complexity of the domain of LV dynamics and the amount of training that a clinical specialist in this area receives, that any single heuristic can capture all the important facets of the evaluation and be successful in all applications; 2) the heuristics are purely quantitative in nature, contrasting with the fact that clinicians, and for that matter humans in general, deal in qualitative or descriptive terms combined with numerical quantities. That is, relational quantities are necessary components of the interpretation process, while numerical ones are secondary. The key here is that a computer system that is to solve the difficult problems present in the domain of LV dynamics interpretation must integrate the above mentioned numerical heuristics as well as consider the symbolic processing aspects of the interpretation. We distinguish our approach from those whose goal is to provide some intermediate visual representation that must still be subjectively interpreted by a clinician (the work described in (Hoehne et al, 1980) is a particularly good example of such a representation). Our goal is to perform this interpretation in much the same way as the clinician does, and to do it in an objective and consistent manner.

In (Aiello, 1983), three incarnations of the PUFF system were compared, each with the same knowledge, but different control schemes. The result of the comparison was that for PUFF's specific problem domain, expectation-driven (what is called model-driven below) was the best strategy, yet it too had drawbacks. Its analysis was strongly influenced by the initial hypothesis, was not able to recover from bad initial states, and moreover could not respond to all input data, only that which was required by the model. The control scheme of ALVEN does not rely on a single mechanism. We recognize that a single scheme may not be adequate for all situations, and thus several interacting dimensions are included. Specifically, our control scheme does not suffer from the above-mentioned drawback, because of its incorporation of model-driven, data-driven and lateral failure-driven search, reflecting traversals of the knowledge base along the IS-A, PART-OF or SIMILARITY dimensions.

Matching is defined as successful if all slots that should be considered for filling are filled and no matching exceptions are raised. Otherwise, the match is unsuccessful. Using this binary categorization of matching, and the relationships amongst hypotheses, a certainty updating scheme based on relaxation processes (Zucker, 1978) is used. Details of this scheme appear in (Tsotsos, 1984), and the definition of temporal relaxation is considered as one of the major contributions of the ALVEN project. Basically, hypotheses that are connected by knowledge organizational relationships that imply consistency support one another, and those linked by relationships that imply inconsistency compete with one another by removing support. The IS-A relationship is in the former group, while the SIMILARITY relationship is in the latter group. The focus of the system is defined as the set of best hypotheses, at each level of specificity, for each set of structural components being considered in the given time slice. The focus, due to the slow change of certainties inherent in relaxation schemes, exhibits inertia, or procrastination, that is, it does not alter dramatically between certainty updates. Both global and local consistency is enforced through the contributions of hypotheses to one another via their organizational relationships.

Examples of the ALVEN system have appeared previously and thus will not be repeated here (Tsotsos, 1985). The results were very satisfactory. Each analysis produced by ALVEN was completely consistent with the reports that radiologists produce for those films. The major difference is in detail. ALVEN produces very detailed descriptions at a number of levels of abstraction. The information that is produced is beyond the capability of analysis by human observation. Moreover, it seems that most of the quantities computed are beyond the capability of the science of cardiology to incorporate into routine patient care. It is encouraging that we can make predictions for quantities and analyses that may also advance the state-of-the-art of heart patient care.

10.4.2. LV dynamics knowledge and its representation

Although there is still much work to be done in the determination of the knowledge of LV dynamics, much can be found in current literature which can be incorporated into our formalism. Two examples will be given. This knowledge is used as a starting point for knowledge base construction only. Moreover, although the exact numerical quantities may differ between imaging techniques, the **qualitative** descriptions do not.

In the series of papers by Gibson and his colleagues, (for example (Doran et al, 1978), (Gibson et al, 1976)), several investigations were carried out that determined quantitative aspects of specific LV motions. In the second paper quoted, the segmental motions of the LV during isovolumic relaxation were examined in normal and ischemic LVs using echocardiography in order to determine dynamic differences between these two cases. Without describing technical details of their method, we will briefly summarize their findings. They discovered that in normal LVs an outward wall motion of 1.5 - 3.0 mm. could be present in any region during isovolumic relaxation. In abnormal cases, that is, patients with coronary artery disease, affected areas show inward motion, 2mm. or more for posterior or apical segments, and any at all for anterior regions, and non-affected areas, due to a compensatory mechanism, may exhibit an increased outward motion of up to 6mm. over normal. The key feature to note here is that the description given does not have a mathematical form at all - it is a combination of quantitative and qualitative measures. The term "outwards" does not specify any precise direction as long as the motion of the segment is away from the inside of the LV. It is not impossible to set up a mathematical model of this; however, the model will be both cumbersome and will bury the pertinent facts in its equations, so that inspection by a non-sophisticated user becomes impossible. The knowledge class for this information (and more) follows:

```
class N_ISORELAX is-a NO_VOLUME_CHANGE with
prerequisites
   subj : N_LV  such that [

           (find ant_mot : NO_TRANSLATION where [
               ant_mot.subj = self.subj.anterior ,
               ant_mot.time_int = self.time_int
               ]
            or
            find ant_mot : OUTWARD where [
               ant_mot.subj = self.subj ,
               ant_mot.time_int = self.time_int ,
               dist(ant_mot.subj.centroid
                    ● ant_mot.time_int.st,
                    ant_mot.subj.centroid
                    ● ant_mot.time_int.et) < 3
                 exception [TOO_MUCH_MOTION with seg
                    ← "anterior" ,
                        direction ← "outward",
                  disp ← dist(ant_mot.subj.centroid
                     ● ant_mot.time_int.st,
                     ant_mot.subj.centroid
                     ● ant_mot.time_int.et) ]
               ]
            ) exception [TOO_MUCH_MOTION with seg ←
                 "anterior", ● direction ← "inward"] ,

          (find post_mot : NO_TRANSLATION where [
              post_mot.subj = self.subj.posterior ,
              post_mot.time_int = self.time_int
              ]
           or
           find post_mot : INWARD where [
              post_mot.subj = self.subj ,
              post_mot.time_int = self.time_int ,
              dist(post_mot.subj.centroid
```

```
              @ post_mot.time_int.st,
              post_mot.subj.centroid
              @ post_mot.time_int.et) < 2
               exception [TOO_MUCH_MOTION with seg
                  ← "posterior",
                 direction ← "inward",
          disp ← dist(post_mot.subj.centroid
            @ post_mot.time_int.st,
            post_mot.subj.centroid
             @ post_mot.time_int.et) ]
      ]
      or
     find post_mot : OUTWARD where [
        post_mot.subj = self.subj ,
        post_mot.time_int = self.time_int ,
        dist(post_mot.subj.centroid
          @ post_mot.time_int.st,
             post_mot.subj.centroid
               @ post_mot.time_int.et) < 3
         exception [TOO_MUCH_MOTION with seg
            ← "posterior",
           direction ← "outward",
          dist(post_mot.subj.centroid
            @ post_mot.time_int.et,
               post_mot.subj.centroid ]
                 @ post_mot.time_int.et) ] ]
    ) ,

    (find ap_mot : NO_TRANSLATION where [
        ap_mot.subj = self.subj.apical ,
        ap_mot.time_int = self.time_int
        ]
     or
     find ap_mot : INWARD where [
        ap_mot.subj = self.subj ,
        ap_mot.time_int = self.time_int ,
        dist(ap_mot.subj.centroid
          @ ap_mot.time_int.st,
             ap_mot.subj.centroid
               @ ap_mot.time_int.et) < 2
            exception [TOO_MUCH_MOTION with seg
               ← "apical",
              direction ← "inward",
           disp ← dist(ap_mot.subj.centroid
             @ ap_mot.time_int.st,
                ap_mot.subj.centroid
                  @ ap_mot.time_int.et) ]
        ]
      or
     find ap_mot : OUTWARD where [
        ap_mot.subj = self.subj ,
```

```
                  ap_mot.time_int = self.time_int
                  dist(ap_mot.subj.centroid
                    ● ap_mot.time_int.st,
                       ap_mot.subj.centroid
                         ● ap_mot.time_int.et) < 3
                    exception [TOO_MUCH_MOTION with seg
                       ← "apical"
                         direction ← "outward",
                        disp ← dist(ap_mot.subj.centroid
                          ● ap_mot.time_int.st,
                             ap_mot.subj.centroid
                               ● ap_mot.time_int.et) ] ]
              )
           ] ;

dependents
   time_int :  with time_int ← (dur of TIME_INTERVAL with
                     dur ← default(0.093*(30/(0.8*HR)))  )
             such that [
               time_int.st \(>= 0.24*(30/(0.8*HR)) ,
               tim_int.et \(<= 0.43*(30/(0.8*HR)) ,
               time_int.dur \(>= 0.08*(30/(0.8*HR)) ,
               time_int.dur \(<= 0.12*(30/(0.8*HR))
                 exception [TOO_LONG_ISORELAX]
              ] ;


similarity links

   sim_link1 : ISCH_AP_ISOVOL_RELAX
      for differences :
          d1 : TOO_MUCH_MOTION where [
                seg = "apical" ,
                direction = "inwards" ,
                time_int = ap_mot.time_int ];

          d2 : TOO_MUCH_MOTION where [
                seg = "anterior" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = ant_mot.time_int ];

          d3 : TOO_MUCH_MOTION  where [
                seg = "posterior" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = post_mot.time_int ]; ;


sim_link2 : ISCH_ANT_ISOVOL_RELAX
   for differences :
```

```
          d1 : TOO_MUCH_MOTION where [
                seg = "anterior" ,
                direction = "inwards" ,
                time_int = ant_mot.time_int ];

          d2 : TOO_MUCH_MOTION where [
                seg = "apical" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = ap_mot.time_int ];
          d3 : TOO_MUCH_MOTION where [
                seg = "posterior" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = post_mot.time_int ]; ;

    sim_link3 : ISCH_POST_ISOVOL_RELAX
       for differences :
          d1 : TOO_MUCH_MOTION where [
                seg = "posterior" ,
                direction = "inwards" ,
                time_int = post_mot.time_int ];
          d2 : TOO_MUCH_MOTION where [
                seg = "anterior" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = ant_mot.time_int ];
          d3 : TOO_MUCH_MOTION where [
                seg = "apical" ,
                direction = "outwards" ,
                disp < 9 ,
                time_int = ap_mot.time_int ]; ;
```

The definition states that for a normal isovolumic relaxation phase to be recognized, normal motions for each segment must be present. There are three main clauses in the definition. The first defines the expected normal motion of the anterior segment, the second for the posterior segment and third for the remaining segment, the apical one. So for example, in the first clause, the definition reflects Gibson's characterization: the anterior segment during this phase, must either not display any translational movement, or could display an outward motion of displacement less than 3 mm. A larger displacement than this in the outwards direction would be recorded as the exception TOO_MUCH_MOTION, with specific additional contextual information recorded as well. In the matching of class definitions to actual observed motions, matching failures are recorded as exceptions. If the anterior segment were displaying motion and it were not outwards, then it must be inwards and this fact, too, would be recorded as an exception. The dependent portion specifies relevant timing information for the temporal placement of the phase within the left ventricular cycle. *HR* is in units of beats/sec. so that the right hand side of the timing expressions is in units of number of images. Also, using the information derived from (Gibson et al, 1976), the similarity links provide definitions of the constraints that must be found if a possible ischemic segment is to be recognized. Note that only the connections to possible ischemic states detectable by considering only the characteristics of the isovolumic relaxation phase, are included above; a set of similarly formed constraints would have to be present for other disease states as well, for those cases where the isovolumic relaxation phase plays a role in their definition. "sim_link2" relates the normal phase to the motion of an abnormal apical segment exhibiting the effects of ischemia. This, according to Gibson's definition, is shown by either the apical region itself having too much inward motion during this phase, and/or one of the other regions (posterior or anterior) exhibiting too much outward motion during the phase. Note that the set of differences does not define a necessary set; any one of the conditions is sufficient.

It should be clear that the above is not complete; it requires the remainder of the definitions for the other phases and motions since the entire definition of each class of LV motion is defined as a hierarchy of abstraction, each level adding more detail to the previous one. Some of the types of information that are represented are volume changes where known for normal phases, ejection fractions, for example; measures of degrees of abnormalities, derived heuristically; and others.

A second body of knowledge of the form necessary for interpretation can be found in (Fujii et al, 1979). In this research eight different clinical cardiac disease states have been investigated with the intent of discovering posterior wall motion differences and similarities among the diseases, as well as global LV characteristics. The diseases are pericarditis, congestive cardiomyopathy, hypertrophic cardiomyopathy, valvular aortic stenosis, aortic insufficiency, mitral stenosis, mitral insufficiency, and systemic hypertension. Normal LV's were also studied. The measurements made for each of the above LV states are stroke volume, rapid filling volume, slow filling volume, atrial filling volume, the percent filling for each of the previous three phases with respect to the stroke volume, posterior wall excursion in total, and for each of the three phases of diastole, as well as the percentage excursion in each phase, diastolic posterior wall velocity, rapid filling rate, LV end diastolic dimension, and ejection fraction. It is, of course, difficult to verify their results. However, they are important - they provide at least a starting point for the further elaboration and verification of such detailed dynamic information. In addition to the large amount of numerical information that has been derived, the significant findings have had attached to them qualitative descriptors - such as whether or not this quantity should be higher or lower than in the normal case. This is rather fortunate from our point of view: the representational formalism that we have designed can handle description via common components and differences very well, and uses such information to advantage during the decision phases of the interpretation. It should be clear from the previous example how such information would be included into the representation, and this fact alone raises another important advantage of this scheme. The addition of information into a mathematical model may require a complete re-definition of the model. In our case, information is easily inserted, as long as one understands the semantics of the representation.

10.5. The CAA project

10.5.1. Overview

The objective of the CAA (Causal Arrhythmia Analysis) system is to establish a framework for the recognition of time-varying vital signals of a complex repetetive nature, such as electrocardiograms (ECGs). The CAA system uses a causal model of the physiological entity so that observed abnormalities of the temporality or morphology of the signal are explained by referring to the corresponding abnormalities of causal events and relationships in the entity model.

In the domain of electrocardiology, this causal reasoning process is especially important because the domain involves causal and temporal knowledge about the cardiac conduction system with which cardiologists analyze clinical observations (ECGs) and thereby provide diagnostic interpretations of abnormal events in the underlying physiological mechanism of the heart. The recognition problem of ECG rhythm disorders, is interesting, above all, because the overall performance of existing ECG programs (for example, IBM Bonner's program) is at most 80% reliable for abnormal ECGs (Hågan et al, 1979) and we believe a basic reason for this unreliability is that current systems lack underlying physiological knowledge to handle the complexity inherent in cardiac rhythms. The ECG wave identification is much complicated by its "antenna" nature of receiving only the aggregated electrical activity of the heart; that is, there is no simple correspondence between signal features and individual electrical discharges in the heart.

Our approach to the problem of building such a system is to construct a knowledge base stratified by several distinct knowledge bases (KBs) from different perspectives of the domain. Its control structure, therefore, supports a guiding mechanism between corresponding concepts in different KBs as well as another guiding mechanism between causally related concepts in each KB. In our representational terms, the former mechanism uses **projection links** and the latter uses **causal links**, and these links together contribute to the generation of hypotheses and the decision of overall interpretations in the recognition of ECG signals. This approach also integrates several established AI techniques. The system inherited the basic control framework from the ALVEN system, and other techniques such as the attention mechanism for specialization and aggregation, which is supported by the implementation of similarity links (Minsky, 1975) and the exception handling mechanism. The hypothesize-and-test paradigm is used as in ALVEN and other systems like PIP (Szolovits and Pauker, 1978) and HEARSAY-II (Mostow and Hayes-Roth, 1978). The knowledge organization method is based on the IS-A, PART-OF, and INSTANCE-OF hierarchies as used in the PSN formalism.

To prove the efficacy of our methods, a prototype system has been designed and implemented using a frame-input PSN system on Franz LISP (Shibahara et al, 1983), (Shibahara, 1985). The prototype with a limited size of knowledge base is being tested and so far has yielded satisfactory results.

10.5.2. Representation of causal connections

Causality may be viewed in various aspects. Rieger and Grinberg distinguished **one-shot causality** where the cause event(s) is required only at the start of the effect event(s) from **continuous causality** where the continuous presence of the cause is required to sustain the effect (Rieger and Grinberg, 1976).

CAA causal links are based on two features of causal connections: first, they specify the existential dependency of an affected event on its causative event(s); second, they impose temporal constraints between causative and affected events. Thus, the affected events cannot occur without the occurrence of the corresponding causative events, with effects temporally following their causes. Since we are interested in representing the dependencies of causal connections among events more precisely, we look at causality from the viewpoint whether a causal influence is internal to a subject or whether it influences other distinct subject(s). One-shot causal links, therefore, are specialized into the following:

1. **Transfer**: the subject of the event normally completes the current event and proceeds to the following event.

2. **Transition**: the subject is forced to terminate its current event and proceed to a new event.

3. **Initiation**: the causative event, due to a given subject, triggers a new event of another subject.

4. **Interrupt**: the causative event, due to a given subject, interrupts and forces the termination of an

event by another subject.

5. **Causal-block**: the causative event of a subject fails to influence an event of another subject due to a blockage of the causal flow.

The above CAA causal links include implicit temporal constraints; thus, causal structures are described more qualitatively without specifying time coordinate values.

Causal events are aggregated at several levels involving arbitrary number of causal links. However, causal links themselves remain atomic lest the semantics of causal connections should become ambiguous.

10.5.3. Use of causal links

To interpret real ECG signals, the knowledge base must contain causal knowledge about normal and abnormal connections among cellular events, which produce particular ECG tracings in the observable signal domain. We represent such causal activities using CAA causal links. Figure 10-2 illustrates a typical ECG tracing for a normal cardiac cycle in (a), its electrical conduction path in an anatomical diagram in (b), and the corresponding causal conduction model with causal links in (c).

In this causal model, short symbols like E0a are used to denote one of four basic events (phases) in a small portion of the cardiac conduction system. These phases are "depolarization" [symbol a], "under-repolarization" [symbol b], "partial-repolarization" [symbol c], and "full-repolarization" [symbol d]. Such basic phase events are successively aggregated into "cycle", "activity", "beat", and "beat-pattern" events in the physiological event component knowledge base to describe more global and complex causal structures.

Note that causal links across beat events (not shown) are TRANSITIONs and INTERRUPTs except pace-making parts (normally, the SA-Node) because the overall oscillation of the conduction system is controlled (or triggered) by such self-oscillating cells. Also, since the current model is rather devoted to supraventricular arrhythmias, the bundle branches are

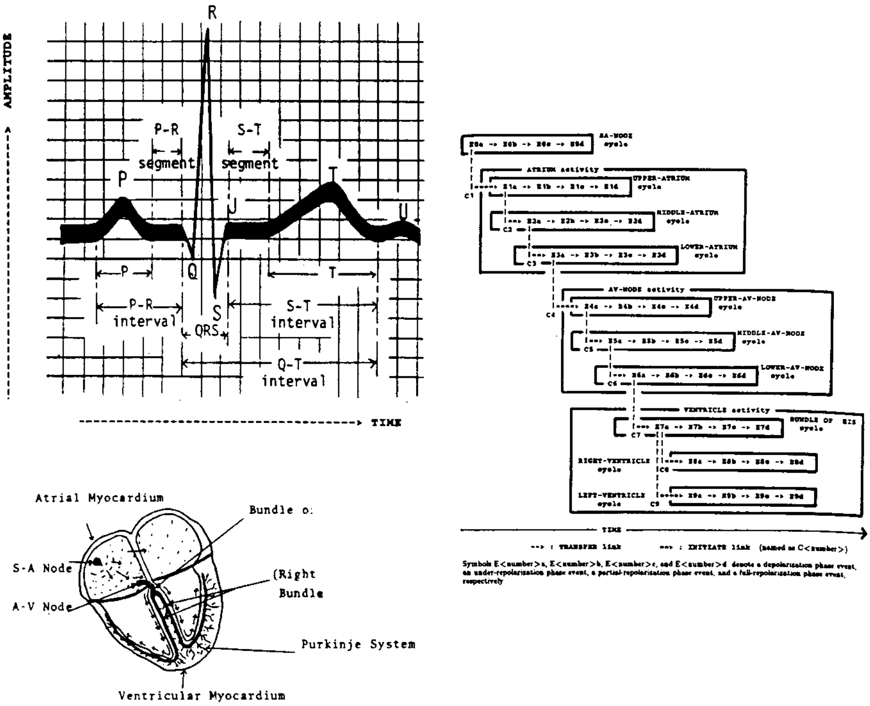

Figure 10-2: A Typical ECG Tracing for a Normal Cardiac Cycle included in the ventricles.

10.5.4. Recent research related to causality

ABEL and CADUCEUS are recent medical expert systems that use causal notions. The ABEL system provides multiple levels of descriptions of medical hypotheses and hierarchically organizes disease structure (Patil, 1981). In the CADUCEUS system, which analyzes differential diagnoses and causal graphs of diseases, Pople proposes sophisticated control links for efficient decision making (Pople, 1982). In spite of the sophistication in expressing causal mechanisms in ABEL and CADUCEUS, these systems do not seem to provide a means to construct a recognition system of time-varying signals, due to the weakness in the representation of precise timing context among events.

Causality has been recently approached from the standpoint of "qualitative reasoning" (Forbus, 1984), (Kuipers, 1984), (De Kleer and Brown, 1984). In this regard, Long's work must be noted (Long, 1983). He introduced qualitative times to describe the causal relations that might or must have taken place. He proposed four causal templates that give an extension of "continuous causality", while our causal links are specialized in "one-shot causality". We have taken a different approach, because original signals are given to the system as real-valued data, and the use of some quantitative analysis is inevitable at the measurement level, so that unnecessary ambiguity is avoided, as Kunz noticed in his AI/MM system (Kunz, 1983).

Based on the methods of multivariate analysis Blum approached causality statistically (Blum, 1982). However, our problem domain includes mostly exact causal relationships. Therefore, we limit the use of statistical standards to the estimation of inherently spontaneous variables such as event durations.

10.5.5. Representation of domain knowledge

Figure 10-3 exemplifies the use of a class frame and causal links. (The dot "." notation is used to specify the component of the referred slot.) This normal activity of the ventricles is decomposed into three cycle events: bundle-of-his-cycle-event, right-ventricle-cycle-event, and left-ventricle-cycle-event. Two INITIATE links represent the conductions from the bundle of His to the left and the right ventricles, respectively.

Note that the information related to the class itself (in this case, the subject part name and the activation type) is given as the instantiation of a metaclass ACTIVITY-CONCEPT.

```
class VENT-ALL-MATURE-FORWARD-ACTIVITY
   is-a VENT-ACTIVITY;
   instance-of ACTIVITY-CONCEPT instantiated-with
                              subject:  VENTRICLE;
                              activation: FORWARD;;
with components
  bundle-of-his-cycle-event: BHIS-MATURE-CELL-CYCLE;
  right-ventricle-cycle-event: RV-MATURE-CELL-CYCLE;
  left-ventricle-cycle-event: LV-MATURE-CELL-CYCLE;
  bhis-rv-delay: NUMBER-WITH-TOLERANCES
        calculate := /* delay set-up expression */;
  bhis-lv-delay: NUMBER-WITH-TOLERANCES
        calculate := /* delay set-up expression */;
causal-links
 bhis-rv-propagation:  INITIATE
  causative-starting-event: bundle-of-his-cycle-
                         event.depolarization-phase-event;
  initiated-event: right-ventricle-cycle-
                         event.depolarization-phase-event;
  delay: bhis-rv-delay;;
 bhis-lv-propagation:  INITIATE
  causative-starting-event: bundle-of-his-cycle-
                           event.depolarization-phase-event;
  initiated-event: left-ventricle-cycle-
                           event.depolarization-phase-event;
  delay: bhis-lv-delay;;
end
```

Figure 10-3: Class Frame for Normal Activity of the Ventricles

Let us examine how the IS-A and the PART-OF principles contribute to the organization of the CAA knowledge base. We take a look at the QRS and QRST waveforms in the ECG waveform KB as examples.

First, the QRST waveform consists of the QRS complex and the T wave; thus, the corresponding class QRST-COMPOSITE-WAVE-SHAPE has the generic PART-OF structure with major components shown in Figure 10-4(a). This generic QRST waveform is specialized into several QRST waveforms in Figure 10-4(b), along its IS-A hierarchy. Let us pick one component from the STANDARD-QRST-COMPOSITE-SHAPE.

NORMAL-QRS-COMPLEX is such a component and this class is itself included in the IS-A hierarchy of the QRS waveforms as in Figure 10-4(c). The orthogonality of IS-A and PART-OF hierarchies is shown in Figure 10-4(d), since STANDARD-R-WAVE-SHAPE is a component of STANDARD-QRS-COMPLEX-SHAPE, and, at the same time, it is included in a local IS-A hierarchy of R-WAVE-SHAPE.

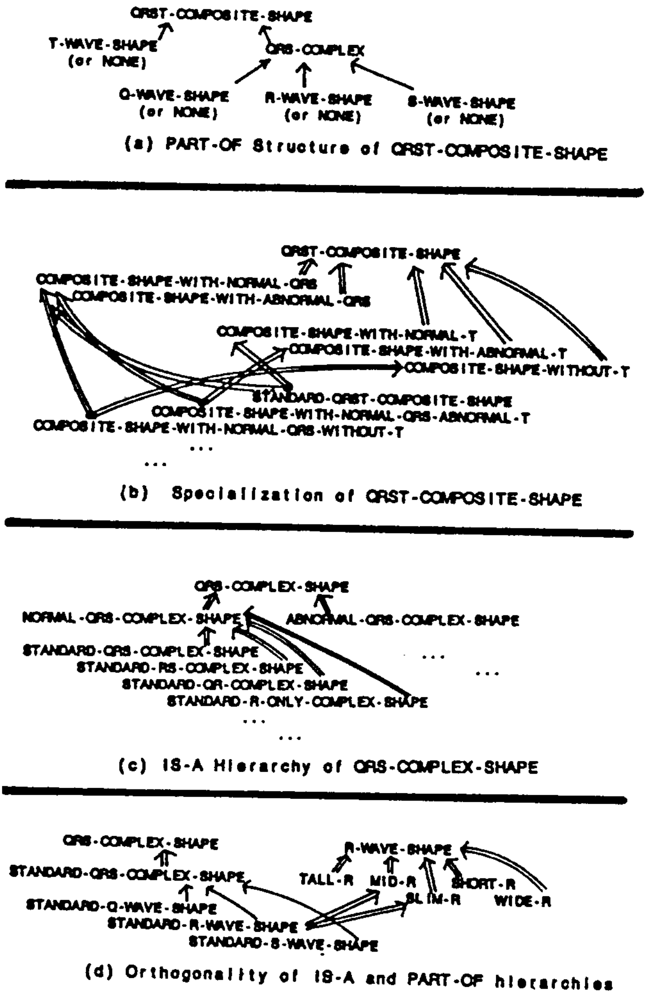

Figure 10-4: The QRST Waveform.

Similarly, various IS-A and PART-OF hierarchies are defined in the physiological KB. Such organizational hierarchies not only contribute to the clarification of the interdependency among domain concepts but also provide guiding knowledge for the recognition process, as discussed later.

Statistical information, commonly used in medical reasoning systems, has particular importance when insufficient information is available about the disease status of a patient (Szolovits and Pauker, 1978). In our case, the recognition system uses statistical standards to produce expectations of unknown attributes of events and to estimate consistencies (goodness-of-fit) of hypotheses. Since statistical standards about a class are not the attributes of any particular instance of the class but the attributes of the class itself, such standards could be defined in appropriate metaclasses and instantiated as properties of the class itself. In other words, event statistics are good examples of meta-knowledge or "knowledge about knowledge", and such knowledge is organized along the INSTANCE-OF axis. In fact, to provide "mean" and "standard-deviation" values to all the physiological phase events, CAA has the metaclass CELL-PHASE-CONCEPT shown in Figure 10-5(a):

In Figure 10-5(a), default functions, MEANFUNC and DEVFUNC, are generic functions that are supposed to generate the mean and standard deviation about durations of phase events. Such statistical standards about phases are function procedures of "subject", "maturity", "phase", and a state variable HR$ (heart rate). Therefore, such a standard, for example, a mean value, is given by the expression "(mean subject maturity phase HR$)" in a particular phase event class (Figure 10-5(b)). In the evaluation of this expression, the slot-names such as "mean" and "subject" are replaced by real properties of the class, such as "MEANFUNC" and "SA-NODE". This is considered as the tailoring process of the general "mean" expression to the definitional context of this event; that is, such statistics may change to fit into each event hypothesis. On the other hand, HR$ is a global variable that reflects the current state of the model, where hypotheses are being instantiated; in other words, such global variables are used to make statistical standards sensitive to the current recognition context. Heart rate, blood pressure and breathing rate are examples of dynamic or time varying global variables, while age-group, sex, race, and types of medications are static global variables. Obviously, the default functions, MEANFUNC and DEVFUNC, may be replaced by

```
metaclass CELL-PHASE-CONCEPT
with components
        subject:  HEART-PORTION;
        maturity: DEGREE-OF-MATURITY;
        phase:    PHASE-NAME;
        mean:     EXPRESSION default MEANFUNC;
        deviation: EXPRESSION default DEVFUNC;
end
```

(a)

```
class SAN-COMP-DEP-PHASE
 instance-of  CELL-PHASE-CONCEPT
   instantiated-with
   subject: SA-NODE;
   maturity: COMPLETE;
   phase:  DEPOLARIZATION;
   mean: ;/* default is MEANFUNC */
   deviation: ; /* default is DEVFUNC */
 is-a PROTO-EVENT
 with
  components
   consistency: NUMBER;
   start-time: NUMBER-WITH-TOLERANCES; /* inherited */
   end-time: NUMBER-WITH-TOLERANCES;   /* inherited */
   duration: NUMBER-WITH-TOLERANCES
        such-that NON-NEG-CONSTR:
          [NOT [GT 0 VALUE$.central-value]]; /* inherited */
  constraints
   duration-estimation:
    (DURATION-ESTIMATE start-time end-time duration
      (mean subject maturity phase HR$)
      (deviation subject maturity phase HR$));
end
```

(b)

Figure 10-5: *(a)* A Metaclass to Describe Phase-Concepts' Own Properties
(b) A Phase Class as an Instance of CELL-PHASE-CONCEPT

any ad hoc functions if necessary.

The role of the function DURATION-ESTIMATE is similar to that of causal links, in that the equation "end-time = start-time + duration" is used to estimate any unknown values among them. In this case, however, the standard mean and deviation values of the duration must be explicitly supplied for the calculation of the consistency (or reasonableness) of the estimated duration value, based on physiological knowledge.

10.5.6. Knowledge-base stratification and projection links

Due to our causal model approach, we distinguish two subdomains: the ECG morphological (shape) domain and the electrophysiological domain. Therefore, the knowledge base of the whole system is stratified by the ECG waveform KB and the physiological event KB. Our idea of stratifying a knowledge base resembles Rich's "overlays", since it provides different perspectives to the problem (Rich, 1981). In our method, however, the linking mechanism between different KBs is biased to recognition purposes.

Projection links have been introduced into the CAA system to relate corresponding concepts in distinct domain KBs. In our model based approach, such links are essential, since they relate temporal and/or morphological abnormalities in waveforms to corresponding abnormalities in physiological causal structures.

The diagram in Figure 10-6 illustrates a projection link that defines the correspondence between the corner point information of a normal QRST waveform and the timings of a normal activity event of the ventricles. This projection link must be defined in the class frame of the normal QRST waveform.

For recognition, the most important aspect of projection links is that they provide guiding paths to map concepts across differently organized KBs and support the synchronization of recognition activities in different domains. In our system, projections from established waveform hypotheses result in the basic data set (hypotheses) in the underlying event domain, on which the recognition of causal events works.

10.5.7. Recognition strategies and control

Signals are processed by three functional modules in the following order:

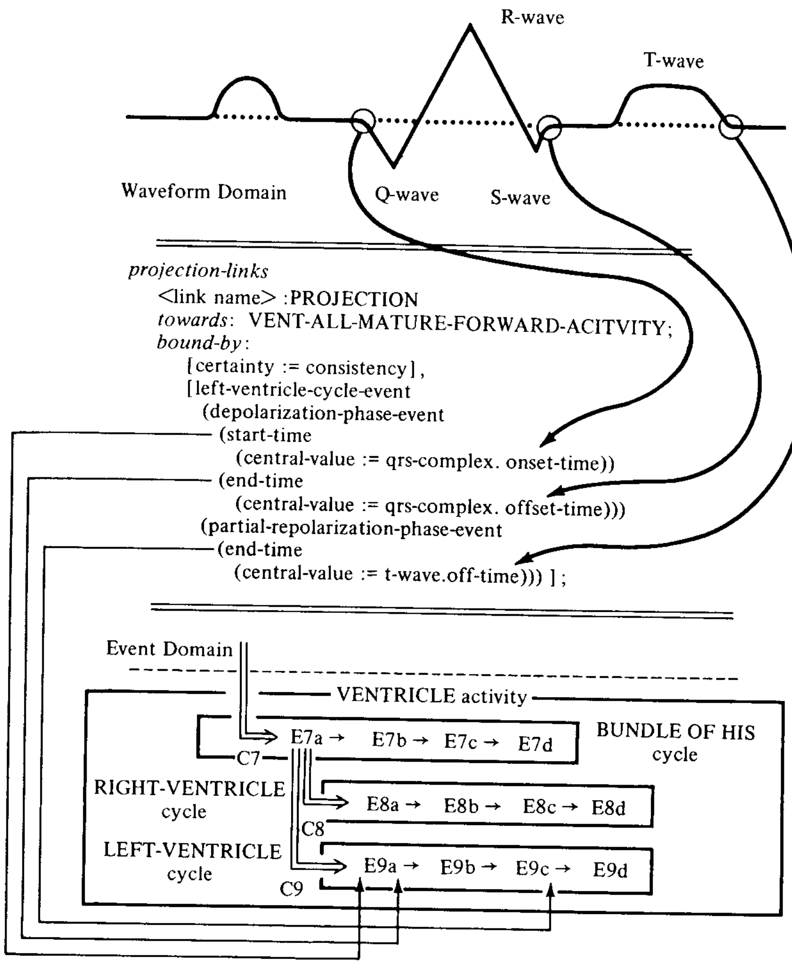

Figure 10-6: A Projection Link

1. The **peak-detection module** extracts wave segments and slopes from sampled ECG input signals and emits peak tokens with the measured parameters. This module uses the syntactic method given by Horowitz (Horowitz, 1975) based on piecewise linearization and parsing techniques using a context-free grammar.

2. The **waveform analysis module**, for each cardiac cycle, forms waveform hypotheses on the peak tokens and refines the hypotheses to describe the

given set of tokens best. Once established, such hypotheses are projected into the physiological event domain to form their corresponding event hypotheses.

3. The **event analysis module** accepts projected events as a starting data set and generates rhythm event hypotheses in a more global context of time to elucidate rhythm abnormalities in the underlying cardiac conduction system. Since most physiological events do not have observable counterparts (waveforms), the event analysis module produces expectations of unknown events, using the causal knowledge of the conduction system and statistical standards of events. If the system encounters a lack of information because of missing waves, it may request the peak-detection module to search for such missing tokens based on the expectation of such waves.

Our recognition strategy is based on the hypothesize-and-test paradigm, in particular, the attention mechanisms of ALVEN. The focus-of-attention mechanism makes recognition (hypothesis formation) proceed from the generic to the specific along IS-A class hierarchies downward. When a class hypothesis succeeds, a focusing action is taken by choosing and hypothesizing an arbitrary specialized class of the successful class. When a current hypothesis fails, the change-of-attention mechanism chooses alternative hypotheses through similarity links, examining the similarity and the difference between classes.

Let us examine how the above specialization-and-aggregation process works for QRST waveforms (see Figure 10-6). After all peaks are detected and measured, the waveform analysis module chooses groups of consecutive prominent peaks with high amplitude and steep slope as *anchoring shapes*. These anchoring shapes are candidates for QRST-COMPOSITE-SHAPE. The wave analysis for an anchoring shape starts with hypothesizing the class QRST-COMPOSITE-SHAPE on the prepared set of basic peak tokens. This class is the most generic for all the shapes composed of Q, R, S, and T waves and only requires the existence of any QRS complex wave as the sole component; thus, this component class, which is again the most generic class for QRS complex waves, is hypothesized, and its instantiation follows, using the prepared Q, R, and/or S wave tokens. If there are no Q, R, or S wave tokens, the hypothesis of QRS-COMPLEX-SHAPE fails, and so does QRST-COMPOSITE-SHAPE. As the second step, one of the specialized QRST composite wave classes under QRST-COMPOSITE-SHAPE is hypothesized, and all its attributes are tested; that is, an attempt is made to instantiate the slot tokens. Since all the specialized classes are connected by similarity links, the system may choose the next appropriate hypothesis using exceptions raised by test results and finally reach the valid hypothesis for the given anchoring shape. The test procedure for each attribute slot, however, triggers an independent process for recognizing the token of the slot. For example, class STANDARD-QRST-COMPOSITE-SHAPE has a slot named qrs-complex and this slot is defined by class NORMAL-QRS-COMPLEX which is an IS-A parent class to classes STANDARD-QRS-COMPLEX-SHAPE, STANDARD-QR-COMPLEX-SHAPE, STANDARD-RS-COMPLEX-SHAPE, and STANDARD-R-ONLY-COMPLEX-SHAPE. Thus, the previous QRS wave slot token of the generic QRST-COMPOSITE-SHAPE must be specialized along the IS-A hierarchy of QRS-COMPLEX-SHAPE, and this process also uses the same procedure in order to reach the most refined QRS complex shape hypothesis. With such a specialized QRS wave token and a separately specialized T wave token, the second step decides the most appropriate hypothesis among QRST composite shapes for the given set of wave tokens.

Similarly, but independently, in the physiological event domain, the specialization-and-aggregation process starts with the most generic beat pattern and eventually provides several specialized patterns as probable overall interpretations.

The recognition starts with establishing hypotheses in the waveform domain. The projection mechanism maps such established hypotheses into the event domain, preparing a set of basic event hypotheses, which are treated like data in the event recognition process.

A beat pattern (rhythm) is a complex time-varying event aggregated from more local events such as beats, activities, cycles, and phases. Causal links in such an aggregated event imply connections among its component events. Thus, once projections are made to some of these components, the system can produce expectations of unknown components from the known components. Therefore, when the system hypothesizes such an aggregated event, it looks ahead or looks back for its component events, which are causally linked to "already-established" component events. Most frequently, causal links are used to locate the temporal positions of "to-be-expected" events by their inherent temporal constraints. This expectation is made by the following basic equality implicitly imposed over starting or ending times of participating events:

<effect-time> = <cause-time> + <delay-period>.

Let us look at the above mechanisms in a small but clear case where a QRST composite wave is seen but the P wave has not been recognized for the current wave group.

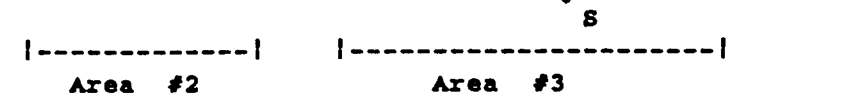

Figure 10-7: The Case and the Interval "Area #1"

Figure 10-7 illustrates the case. The interval "Area #1" is the probable area where a P wave would appear if the beat is a normal sinus-pacing beat. To estimate such an area under a particular beat hypothesis is important, since the peak-detection module may search for a P wave intensively in this area, again.

The area is estimated using the projection and the expectation mechanisms in the following fashion:

1. A hypothesis of NORMAL-QRST-COMPOSITE-SHAPE is established.

2. A projection to a normal ventricle activity event (Figure 10-6) is undertaken, as follows:

   a. The onset and offset times of the QRS complex are bound to the starting and ending times of the depolarization phase of the left ventricle. The off-time of the T wave is bound to the ending time of the partial-repolarization phase. These phase events are generated immediately, and two other phase events are expected by three TRANSFER causal links and event statistics. Thus, the left ventricle (LV) cycle event is generated.

   b. By the INITIATE causal link to the Bundle of His (BHIS) and subsequent TRANSFER links, the BHIS cycle event is generated. Also, by the INITIATE link from the BHIS to the right ventricle (RV), the RV cycle event is generated.

   c. With the above three cycle events, the projection to the normal ventricle activity event is completed.

Expectation of AV-Node activity, Atrium activity, and SA-Node activity under a hypothesis of the normal sinus-pacing beat (Figure 10-2(c)) is carried out as follows:

a. The INITIATE link C7 is invoked to expect phase E6a; then E6b, E6c, and E6d phases are expected by three TRANSFER links· and, finally, the lower AV-Node cycle event is generated. Similarly, using C6 and C5 INITIATE links, the middle and upper AV-Node activity events are generated. Thus, the AV-Node activity event is formed with these component cycle events.

b. Starting with the INITIATE link C4, the atrium activity event is expected in the same way as above, and, next, the SA-Node cycle event is expected.

c. A hypothesis of the normal sinus-pacing beat is completed.

Under this hypothesis, the on-time and the off-time of the P wave correspond to the starting time of the upper-atrium cycle and the ending time of the lower-atrium cycle, respectively. Therefore, the search area for a probable P wave is given as the interval between these times (for example, from 110 +/- 16ms to 40 +/- 15ms before the QRS complex). The request of the search for the P wave is fed back to the peak-detection module to repeat the detection with different sensitivity parameters.

The above CAA expectation mechanism is characterized by the following features:

(1) The expectation is made from the known to the unknown, forward or backward in time, and upward or downward in a PART-OF class structure.

(2) The expectation proliferates to make a closure of temporal and/or structural dependencies and complete the PART-OF structure of the hypothesis.

Projections are made in the following fashion:

(1) Projections may be made between differently structured classes, as seen in Figure 10-6.

(2) To eliminate unnecessary instantiations of projections, any projected class is instantiated only when a current global hypothesis requests the class as a component.

To recognize a periodic or successive arrhythmia, its repetitive behavior is defined by the recursive definition of beat-pattern frames. By such a frame, recognition may proceed one beat to the next along the time axis instantiating successive beats to form the beat-pattern.

In the process of forming beat-patterns, causal links between adjacent beats allow the system to verify the causal relationship that governs the pace-making mechanism on a beat-to-beat basis. The overall consistency of a beat-pattern is calculated based on the consistencies of these causal links and beat components.

As well as the causal consistency among beats, overall characteristics and tendencies are observed and used to recognize individual arrhythmias. For this purpose, most beat-pattern classes include a component that monitors the changes of variables from one beat to another. A typical example is to monitor the change of the R-R interval or the P-R interval.

In arrhythmia beat-patterns, similarity links must also be defined to relate beat-patterns that have some features in common and handle situations where one or more matching exceptions have been raised. Figure 10-8 shows ECG wave configurations that correspond to three different AV-Block arrhythmia patterns and the matching exceptions used by similarity links. Such similarity links between repetitive beat-patterns enable the system to switch beat-pattern hypotheses from one pattern to its alternatives [according to the exceptions raised during the instantiation of the pattern hypothesis.]

The recognition of particular arrhythmia patterns such as the above AV-Block beat-patterns must be initiated by more general classes in the IS-A hierarchy they belong to. The most generic class for repetitive arrhythmias is REPETITIVE-RHYTHM-PATTERN, and this class is immediately specialized according to the heart rate into one of three rate-specific classes: FAST-RHYTHM-PATTERN, MODERATE-RHYTHM-PATTERN, and SLOW-RHYTHM-PATTERN. If we assume a normal heart rate between 60 and 100 beats per minute, MODERATE-RHYTHM-PATTERN is selected And one of its more specialized classes must again be chosen. Normally, the first choice is NORMAL-SINUS-RHYTHM-PATTERN, because it represents the most generic rhythm that has only NORMAL-SINUS-PACING-BEATs. If any abnormality is found in the recognition of such normal beats, other rhythm pattern(s) are triggered through a similarity link, which detects the

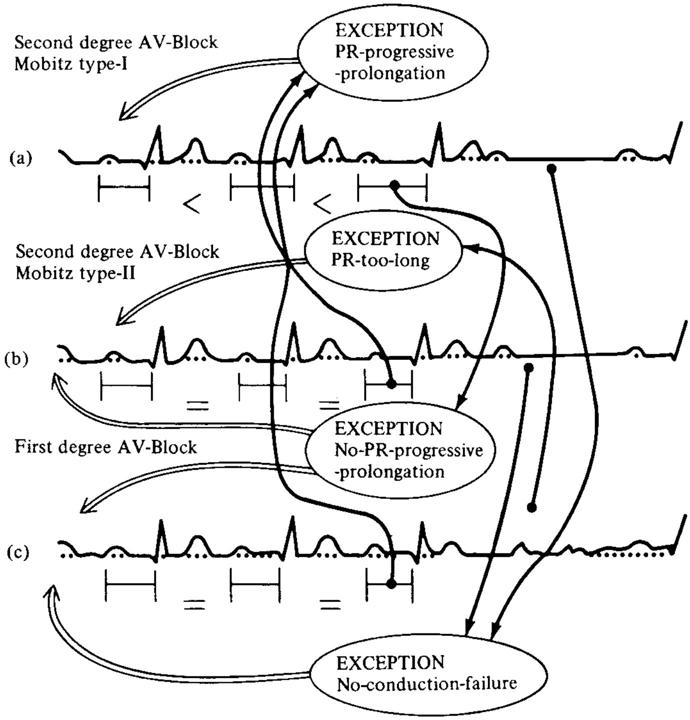

Figure 10-8: ECG Wave Configurations

abnormality. For the cases of AV-Blocks, an exception must be raised by the prolongation of the atrium-ventricle-interval in the recognition of one of component beats. Then the similarity link which contains this exception condition triggers a rhythm pattern AV-PROLONGED-RHYTHM-PATTERN, which is the immediate IS-A class of the above three AV-Block beat pattern classes.

To recognize particular arrhythmia patterns, the specialization-and-aggregation process must be initiated with the most generic class for repetitive arrhythmias. The final interpretation, therefore, is given by a set of all survived beat-patterns with overall consistency factors. The consistency is calculated using event statistics and a test-score function, which is similar to a fuzzy constraint in (Zadeh, 1983a).

10.6. Conclusions

Our basic conclusions lie in the claim that frame-based representations are appropriate for complex time-varying signal interpretation tasks. We have presented aspects of representation, knowledge organization and control, that have led to successful implementations of two systems, ALVEN and CAA, that deal with temporally rich medical signal domains. In the case of CAA, a further contribution was described, namely the deep model of the heart's electrophysiology, and a mechanism, projection, was presented that allows for relating signal characteristics to conceptual entities responsible for generating those signals. A final basic claim is that it is not the frame nature of the knowledge representation per se that has been responsible for the success of these systems, but rather the relationships of the frame organization, that is, the IS-A, PART-OF, INSTANCE-OF, SIMILARITY, and Temporal Precedence relations, that drive the control. These relationships drive the control structure as well as provide desirable knowledge structure.

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