AN INTERACTIVE KNOWLEDGE-BASED SYSTEMS APPROACH TO CARDIAC IMAGE DESCRIPTION AND ANALYSIS*

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ABSTRACT

There have been many systems which have been used in analyzing cardiac images of various types. A common feature of systems which attempt automatic image recognition is that their algorithms are applied locally, that is, that border recognition is accomplished by examining the neighbourhood of a point on a single picture frame. Although some systems are provided with primitive information about where to expect a border, they have a lack of real "knowledge" about the behaviour of features in the image. Our approach is based on the use of interactive systems to obtain and structure knowledge about the characteristic behaviour of portions of the ventricular border in a variety of normal and abnormal wall motion situations. This knowledge will be organized into a "knowledge-base" which abstracts and integrates the essential features of ventricular segmental wall motion. We will then study the feasibility of using the knowledge-base to guide low level algorithms in recognizing the border and a high-level algorithm in producing qualitative descriptions of image behaviour. We also hope to use the system to analyze families of images in order to obtain additional quantitative data to refine and enhance the knowledge-base.
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INTRODUCTION

In the last 20 years many techniques have been proposed and implemented for the purpose of extracting quantitative data from cardiac images. Until recently most work was concentrated on the analysis of either film or video images obtained in X-ray contrast studies of the left ventricular chamber. More recently, images from other sources have come to be the target of such systems including: echocardiographic images especially of the 2-dimensional type, scintigraphic images obtained by gamma camera imaging of circulating nuclear-labelled material, and 3-D CTT images collected in real-time.

A variety of manual systems[1,2], semi-automatic systems[3,4,5] where border recognition is carried out by the human operator with computation handled by the computer, and automatic systems[6,7,8] where both border recognition and computation is attempted by the system, have been developed in answer to the need of processing cardiac images. The relatively recent availability of 2-dimensional echocardiographic imaging systems with their potential to allow frequent non-invasive cardiac performance studies has put additional pressure on researchers to develop systems which allow quick processing and quantitative analysis of large volumes of images.

To date, however, there is no really successful system capable of measuring even all angiographic images, let alone the often lower quality non-invasive images. This is because image quality is highly variable and systems fail on all but the best images. In addition, border detection algorithms are easily deterred by obstructing objects such as overlying anatomical structures and confused by structures in the heart itself such as the papillary muscles. These problems are perceived by us to be caused by the failure to provide guidance to lower level border detection processes as they attempt to search for the border. Also, current systems have no means of discovering when they have made a mistake since there is no higher level domain-related knowledge against which their activities can be evaluated and checked for reasonableness.

Some systems allow an operator to interact with them and to correct errors detected by him. Unfortunately, this operator cannot merely provide guidance but must completely take control of the system, correct the error, and complete the entire operation.

Finally, current systems are unable to produce qualitative descriptions or summaries of data relevant to what they find. This is because the system does not, at its highest level, have any knowledge of the potential behaviours of ventricular wall segments and consequently is unable to assemble a description relative to such knowledge.

In summary, we feel that automatic systems have failed because they do not have adequate domain-related knowledge which can be used to guide the border recognition process and help disambiguate between artifactual border motion and abnormal border motion. Our work, although in its early stages, is directed toward producing such a "knowledge-base", a descriptive model of all types of ventricular segmental behaviour. In order to do this, we are developing methods of reducing the masses of raw data which result from an image study to both quantitative summaries and descriptive or qualitative formulations. We are also investigating the possibility of producing a system which is able to use this accumulated knowledge about image behaviour to guide the border recognition process and to augment the knowledge-base with new knowledge obtained during interactions.

RELEVANT PAST WORK

Knowledge Bases and Knowledge-based Recognition

Artificial Intelligence (AI) techniques have been applied in medical applications with a number of particularly successful systems such as MYCIN[9] and Internist-II[10], and in other applications for knowledge-based problem-solving and image analysis[11,12,13,14]. AI research has shown that such a problem-solving system can be decomposed into 2 conceptual units. One unit is the explicit representation and incorporation of problem-domain knowledge and the other unit is the set of algorithms which use this knowledge in order to solve problems posed to the system. The collection of domain-dependent information is known as the "knowledge-base".

Several issues must be addressed and tradeoffs considered during the construction of a knowledge-base.[15,16] Some knowledge is better expressed in a passive way in terms of data structures, while other knowledge is more usefully represented in an active manner in terms of procedures or processes. For a non-trivial problem the knowledge-base is large and exceedingly complex, so it becomes imperative to organize its data structures and procedures efficiently.

In terms of the algorithms which use the knowledge-base, many different types of procedures are possible[17,18]. Recognition may proceed "top-down" or "bottom-up" depending on whether the algorithm starts from the concepts to be recognized and proceeds with the recognition or starts with the image to be analyzed and proceeds with an analysis that eventually associates the image with a concept. "Middle-out"or heterarchical analysis is also possible[19]. An algorithm may maintain several active "hypotheses" concerning what is happening in the image being analyzed, and then explore the most likely hypothesis. This process of maintaining several active hypotheses only ends with the confirmation of one of them. In this sense image recognition in terms of normal or abnormal behaviour is not unlike other problem solving tasks such as puzzle solving or theorem proving. Of course, the recognition procedure must make heavy use of the knowledge-base to guide the search. A properly designed and properly used knowledge-base can lead to a great reduction in the number of possibilities that need be considered by the recognition algorithms, much in the same way as the search for a move by a chess grand master is much more directed and selective than that of an amateur. Needless to say, the task of designing a knowledge-base and recognition algorithms that use it is a non-trivial one.

The question then arises: why should we use AI techniques for ventircular image processing? Previous attempts not using a knowledge-based approach have failed because they operate blindly and only locally on the scene. Filters, thresholding techniques, and other locally active algorithms, not supplemented by "higher-level" procedures, lack global information to guide decisions about where the border is. Thus, it is no wonder that current systems do not attempt to classify or recognize various types of wall motion, nor are they capable of formulating qualitative descriptions or for that matter of outputting more than voluminous measurement data.

Our preliminary work in this area seeks to test the hypothesis that AI techniques can provide solutions to these weaknesses of current systems.

In particular one might consider the problem of guiding the border recognition algorithm in the face of superimposed structures such as ribs or internal structures such as papillary muscles. If the border recognizer were guided by a high-level process which could provide an expectation of where the border should be and where various anatomical structures might be (for instance, the papillary muscles), errors in the vicinity of such structures can be reduced significantly.

Additionally new developments in motion understanding systems may provide mechanisms for recognizing normal and various abnormal segmental wall motions in the cardiac image.

Motion Understanding

"Motion understanding" is a term coined for the methodology by which a computer system can process an image sequence (for instance a film) selected from a particular domain (for instance a ventricular contraction cycle), and "understand" the motion of objects or subobjects that appear in the sequence[20,21]. Such a system is said to understand motion if:

a) it can follow each object or subobject from image to image; and,
b) it can provide a high-level description of the motion(s) involved using the usual tools of motion description -- verbs, adverbs, etc.

The general methodology used by a motion understanding system will now be briefly outlined. A motion understanding system is composed of several components. The first, and probably most important, is the knowledge-base (KB) which contains all relevant domain-dependent information. It includes physical descriptions of the objects or portions of the objects participating in the scene and their motion capabilities, the levels of abstraction of motion from sequences of points to motion verbs, the process for abstracting, and information on how to distinguish between normal and unexpected or abnormal motion (in the case of the ventricular image studies).

The second component is a process which uses and coordinates the knowledge in the KB. This process will be called the "coordinator". The "coordinator" process must be able to maintain a "scene database" in which all data captured from the image sequence is stored, including the objects and their location and motion. This information is stored at different levels in the system. At the bottom level are the objects in the image sequence and their sequence of locations in the image. Higher levels in the system provide descriptions at increasing degrees of abstraction, the number of which depends on the type of de-

scription required.

Another function of the coordinator is to control the recognition process. Information about the recognition process is found in the KB, but a recognition algorithm must use or execute this information. This algorithm, in general terms, usually proceeds as follows. For every object in the scene, there exist several active parallel hypotheses (stored in the KB) as to the type of motion it exhibits. The object's current motion parameters (location, trajectory and speed) obtained from a particular image, and the motion expected by each hypothesis (there will be several hypotheses at any time), are combined to produce an expectation window for the object's location in the next image. Thus there are several expectation windows (with possible overlap) for the object's next location. These windows are passed down to the low-level process (described later). The low-level uses these predictions to locate each object in the scene. New locations for the objects are then passed back to the recognition algorithm and the coordinator. These are used to determine which hypotheses are still valid, which should be terminated, and whether any new ones should be activated. The scene database is also updated. The motion hypotheses actually provide the abstract descriptions for the motions. Each hypothesis is structured so that when it is verified, it adds a level of abstraction to the description.

In addition to the KB and the coordinator, there is a third component we have called the low-level (LL). This is an independent process which can communicate with the coordinator and the recognition algorithm. It must contain an algorithm for finding objects using the expectation windows provided by the coordinator and the recognition algorithm as guidance. After finding the object it passes their locations back. The LL is also capable of asking for further assistance from the coordinator in cases where it cannot find a border within the expectation window. In cases where the coordinator is not very confident about the window, the LL may be instructed to enlarge the search space until the border is found. In cases where the LL simply cannot find a border, the coordinator may instruct it to use an expected border for the segment and then proceed with the remaining recognizable portions of the border.

The techniques of motion understanding seem appropriate to the analysis of serial ventricular images. The LL could consist of any one of the better border-following algorithms modified so that it can accept an expectation window in which to digitize and search for the border. The knowledge-base would contain information such as the various possible ventricular shapes, the motions, possibilities for each of the wall segments, and the various abstract terms necessary for motion description.

One important problem in this application is that potential motion patterns of ventricular wall segments are not known and must be determined. We are implementing a series of interactive systems to capture data from human-outlined ventricular borders in order to build up the necessary knowledge-base, one of which is partially implemented and currently being extended. These will be described later in this paper.

Interactive Motion Analysis

The search for automated border recognition was a response to the apparent impossibility of manually digitizing the desired data. Current manual techniques, for example, require one to four hours of a technician's time to trace borders in one second of a visual record. A recent innovation, however, suggests that we again explore manual data entry, but now from a different point of view.

The point of view, articulated by Robert Futrelle in his GALATEA system[22], was developed in response to the need to analyze image records where structures were not easily visualized in any individual frame but only in the motion sequence. Movies of slime molds, for example, are filled with motion, but there is nothing but a cloud of particles visible in an individual frame. Techniques were therefore developed to trace motions of component parts of the image as the movie is being played back in real time or in slow motion. These techniques appear relevant to ventricular motion sequences because of the poor quality of the images and because of the difficulty of developing cost-justified completely automatic border recognition systems.

OUR APPROACH

Thus far, we have accomplished the following:

1) Implemented a primitive system for digitizing borders and critical features of cineangiograms on a frame-by-frame basis;

2) Begun design of a sophisticated motion analysis system that will allow coherent data entry of entire motion sequences, not merely individual frames;

3) Begun design of a prototype knowledge-base;

4) Implemented a primitive low-level border recognition process; and

5) Begun design of higher-level border recognition processes.

We must stress that most of this work is very preliminary and is only intended as an example of our approach.

A Primitive Data Collection System

A primitive system has been implemented to begin the actual knowledge acquisition process. The purpose of this system is to gather ventricular segment behaviour information from a large number of sample films whose segments exhibit various forms of abnormal and normal motion. The system permits digitizing the images and inputting the borders to the system.

The system displays the digitized static film image on a video monitor. Using a digitizing tablet, the user can draw heart borders superimposed on the image. The system is designed for the input of multiple independent segments and for

the efficient input of tantulum screw motion, one of the few ways of observing true 3-dimensional motion of a fixed point in the ventricular wall. A certain amount of patient-related data is also captured.

Once the border is acquired, the system is able to calculate the more popular quantitative cardiac measures and to have the border processed by feature recognition algorithms. Output of both raw and processed data is supported to allow checking of the results.

Motion Analysis of Cardiac Images

Work is proceeding on a variety of output techniques which allow superimposing the human- or system-recognized border on the source image for viewing statically and during real-time playback. One specific interest in terms of input is concentrating on individual segments and tracking the segment through time relative to some frame of reference as opposed to completely outlining the border in any given frame. Tracking a single segment through multiple cycles and moving quickly from frame to frame enables the operator to better discern the location of the segment than does the outlining of a whole static image at once. After acquiring the information on any given segment, the system will then proceed to allow the operator to measure other segments until a complete set of segments is measured on the sequence of images.

In this regard the techniques of superimposing computer-controlled film and computer-output line graphics, or the possibility of mixing either digital or analog video playback with digital video border information is being investigated. Ultimately, in our opinion, the ability to accurately indicate the segment border and describe its motion will depend upon the ability to play back the superimposed source image, guides for the selection of segments, and the border segments themselves in real-time.

A Prototype Knowledge-Base

A complete description of LV wall motion is both static and dynamic and requires several levels of abstraction. The tentative data description will be outlined beginning at the highest level and proceeding downward.

The LV wall is first divided into standard wall regions depending on whether the LAO or RAO view is displayed in the film. These regions can be described using terms from geography. If the LV border is considered to be a lake with the LV wall land surrounding the lake, then the border can be described as a sequence of bays, capes, peninsulas, etc. Each geographic feature is defined by several descriptors such as length, depth, and start and end locations and such descriptors can exist at both local and gross levels.

This interim general qualitative shape description method is being experimented with as no other is available in the cardiac literature. In going from local to global we have 3 levels of abstraction to the static description.

For the dynamic description, 4 levels are defined. At the highest level are the successive phases of the left ventricular cycle (see Figure 1). These phases are described in very general terms such as the opening and closing of the valves, gross size changes of the LV, blood flow, temporal connections, and default start and end times for each of the phases. At the next level down, size changes are further refined in terms of changes in the LV gross wall segment features using verbs such as stretch (fill), shrink (empty), rotate, translate, etc. Several verbs may be necessary to describe one complex motion. These verbs are further refined at the third level. The motions of detailed features comprising a wall region are described using the transformation predicates rotate, translate and stretch each having both horizontal and vertical components[23]. The values of the components of these predicates aid in selecting the proper verb for the next higher level. Finally, at the lowest level are the picture elements making up features whose motion is stored simply as a sequence of points. It should be noted that the number of points in a feature is not constant.

Another important part of the knowledge-base is the LV part hierarchy. In this hierarchy all parts of the left ventricle would be included, with relative locations of each and their functional connections. The wall segments are related to parts in this hierarchy so that approximate locations of all important components of the border can be found.

We have also been studying the problem of representation relating to the knowledge-base. Methods of representing both 2-dimensional and 3-dimensional borders are being investigated. In addition to the representation of shape, methods of representing motion and the inherent variableness (fuzziness) in the data are being explored.

A Prototype Higher Level Process

Algorithms for the recognition of geographic features, for following such features from image to image, for dealing with the appearance of new features and disappearance of features from an image, and the selection of motion parameters and verbs are under development.

An experimental program is being implemented which uses heuristics in recognizing features. In the first image of a sequence a set of features is determined for the outline. Using the expected motion, the new feature sequence for the next image is computed. The new features are computed by applying the transformation predicates on the old features and correcting gaps which may appear between the now altered features. The features not shown in the new sequence have terminated and new ones have started for this image.

A Prototype Lower Level Process

A prototype LL has been implemented[24] and will

briefly be described here. A sequence of images is digitized from film and provided as input. The coordinator guidance is provided, in this demonstration system, by a human operator. The algorithm used for border detection is based on those described by Warner[6] and Tasto[25] and is modified as follows. Into the formula for determining the likelihood of the existence of a border point a prediction term which can have variable weighting has been incorporated. This prediction in effect is the expectation window provided by the coordinator. Using this prediction, along with the standard features of the border detector described by Warner, border points are determined. After a predetermined number of border points have been chosen or where the LL determines it is lost (by noting a highly irregular curvature), the algorithm stops and passes this segment of points to the high level (human operator) for verification. The coordinator verifies that the segment is in fact part of the border or that the LL is lost for one reason or another. If the LL is lost, the coordinator provides a higher confidence level (i.e. a smaller expectation window) for the predicted border in that segment and instructs the LL to go back and attempt to determine the border in that segment again. This process of verification and guidance continues until the entire border has been found. In desperation, the border segment is forced to be the one with the greatest expectation.

Interactive Systems Aspects

The interactive aspects of system design are important since it is necessary that the human operator be able to efficiently use the system to analyze large numbers of films in an attempt to get good descriptions of classes of motion.

In addition, once it is possible to integrate an automatic border detection process into the system, it is desired that adequate output exist so that the performance of the system can be monitored. Where the system is stymied, and the knowledge-base is unable to discern whether the border segment is correct, or if the operator discovers an error, it will be necessary to interact with the system to correct at least the segment found to be in error. It is desired that the human operator be able to correct or guide the recognition process and allow the system to continue in operation as before the error. Furthermore, the system should be able to use the knowledge gained from the human correction process, for instance in recognizing the same segment in the next frame. Thereby the number of interactions with the system would be greatly reduced and the knowledge-base's sophistication with regard to handling at least that type of error would be enhanced.

SUMMARY, UNRESOLVED ISSUES AND CONCLUSIONS

In summary we have presented the problem of ventricular image analysis and discussed previous attempts at its solution. Difficulties encountered in these attempts have suggested a research strategy incorporating areas of computer science not previously applied to the problem or not applied effectively enough.

Specifically we suggest:

1) That we attempt to formalize our understanding of motion of both normal and abnormal ventricular wall segments in a knowledge-base.

2) That we use recently developed methods of motion description and analysis in formulating high level qualitative descriptions of the actual events occurring in the image.

3) That we build a sophisticated interactive graphics system to facilitate the construction of, experiments with, and refinement of the knowledge-base.

It must be emphasized that we are just beginning this effort. Many issues remain to be resolved; much work remains to be done. Multiple independent approaches in terms of implementation must be integrated. A great deal of research must yet be accomplished and this research can be clustered into 3 categories:

1) The representation of the knowledge-base. Specifically, how is the knowledge-base to be represented? How are the "high-level" concepts such as the shape of the ventricle in 2 and 3 dimensions to be described? How is the motion of the segments to be described? How are concepts such as structure, relationships, and functions to be represented? What information should be stored declaratively and what procedurely? How is the inherently fuzzy nature of the data to be handled?

2) Creation of the knowledge-base. How will the knowledge-base be created? How can we extract from our library of thousands of unanalyzed cineangiograms and from our cardiologists the data and the descriptions with which we must structure and fill the knowledge-base? What type of system is optimum for the input of the knowledge-base information? How will dynamic graphics be used in the playback of borders and of measured data?

3) The use of the knowledge-base. How precisely will the knowledge-base be used in guiding the recognition process and in formulating descriptions? How will its contents be displayed both in relation to a particular frame and as an abstraction of a class or normal or abnormal motion so that, for instance, a cardiologist can verify its correctness or consistency and even augment it? How exactly will we achieve the semi-automatic analysis whereby we interact with an automatic algorithm correcting and directing it? How will the system acquire knowledge from the interaction when a border segment is found to be in error?

What we have initiated is a long range program of bootstrapping ourselves toward an ultimate formal description of ventricular motion in a variety of normal and abnormal situations. This description will be expressed as a particular kind of computer model, a knowledge-base, a model whose execution can aid in its continued refinement and improvement. An integral part of this process of refinement and improvement will consist of the input of skilled users who through interaction

with the computer system will be forced to make their insights explicit, to really formulate what is occurring in terms of ventricular segmental motion, and to consider where and how to add these to the knowledge-base.

We hope, in spite of the many problems to be solved, that this approach gives us sufficient breadth and depth to proceed not just with the problem of automatic image recognition, but with a much more important issue: that of modelling the human ventricle, at the present time descriptively, but ultimately causally. If it is possible to approximate such a model, then this knowledge-base will become a medium for hypothesis formulation and testing that aids a very difficult domain of scientific exploration, for little is known about segmental ventricular behaviour, and descriptions of this behaviour have always been vague and consequently very much less valuable than they could be.

In short, very much is to be done, in fact virtually everything. But what other approach will get us further than current systems? What other approach can truly deal with poor image quality, for instance, in the case of scintigraphy? What other approach will take us beyond simple recognition and into description? What other approach might conceivably provide a tool for modelling ventricular segmental performance to help us to really understand dynamic ventricular behaviour?

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CODES FOR FIGURE 1

st - start time	E - element
et - end time	and - conjunction
o - object	same - approx. equal to
init - initiates	LV - Left Ventricle
dir - direction	LA - Left Atrium
gt - greater than	MV - Mitral Valve
vel - velocity	AV - Aortic Valve
ct - changes to	

CAPTION FOR FIGURE 1

Blank nodes signify undetermined times. We don't really care about value as long as restrictions hold. Time values given are default values used as a guide, not as necessary for each case.

The top part of the figure gives the phases of the ventricular cycle connected to the time line. After time = 80, phases repeat.

The lower part of the figure gives the events which occur during one cycle. The events are connected to the time line, there being only one time line, not several distinct nodes for each value. The lower part also shows how an abnormality of function is handled, for instance the flow event in the lower left section would trigger mitral regurgitation if et is appreciably greater than st.

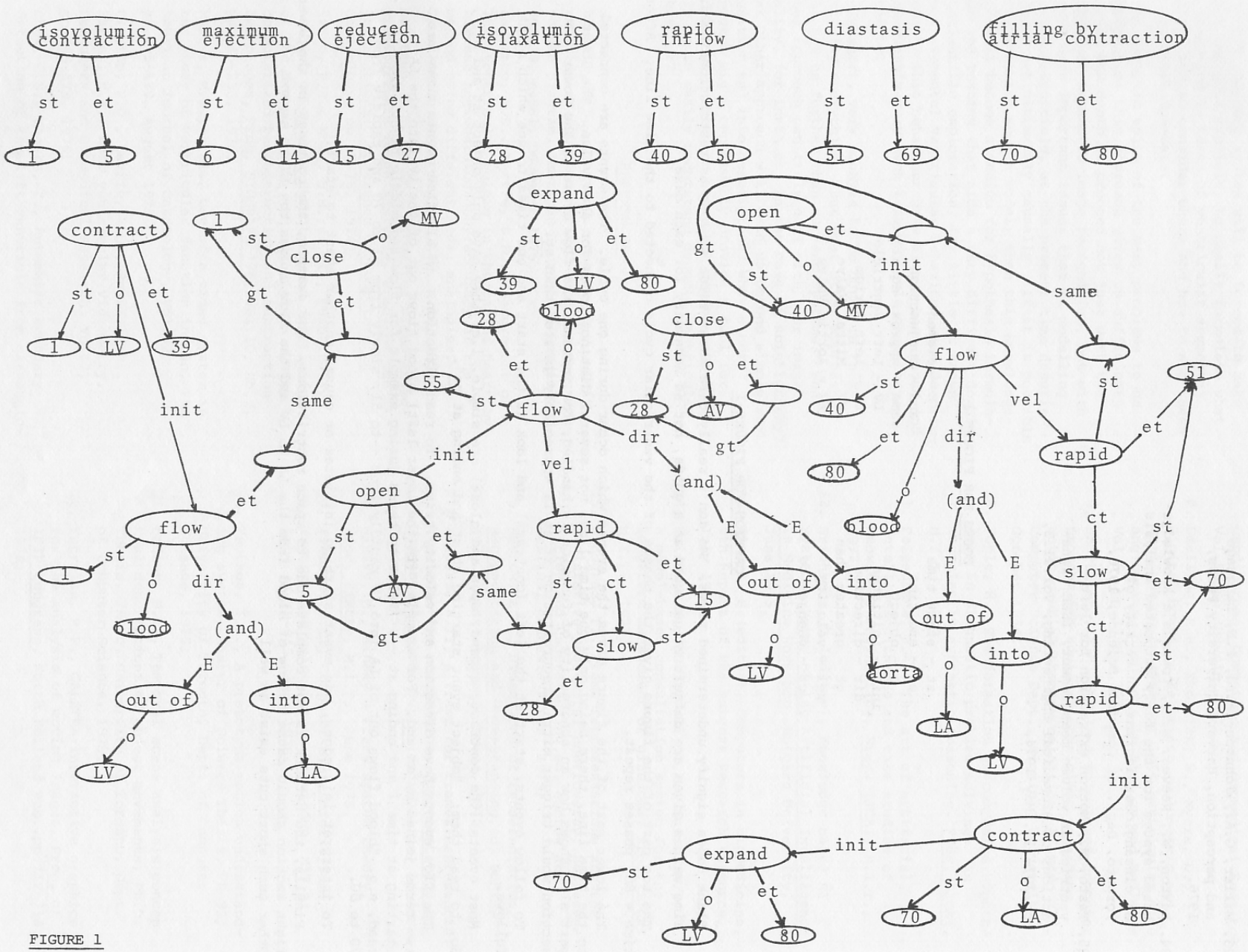
To follow events, start at the left (contract) and look at the start and end times to see which event follows.

Most events (the contract, expand, open and close) are simple, i.e. they have only object st and et. So, to read them: "object event starting at st and ending at et".

The flow events have direction and velocity terms. To read direction: in all flow events there are two terms joined by an and. For example, (in the lower left) blood flows out of the LV into the LA starting at time 1 and ending at --. Velocity terms (using example for flow and middle right) are read, e.g. "blood flows out of LA into LV rapidly from --to 51, slowly from 51 to 70 and rapidly from 70 to 80.

To interpret init edges, one event starting initiates or causes another event to start.

Finally, the network is not complete due to space restrictions. For example, the contract in the lower right section should cause a flow of blood from the LA to LV and the flow causes the LV to expand. Other such short cuts exist as well.


isovolumic contraction
maximum ejection
reduced ejection
isovolumic relaxation
rapid inflow
diastasis
filling by atrial contraction
contract
close
expand
open
flow
rapid
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out of
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FIGURE 1