Spatial Anatomic Knowledge for 2-D Interactive Medical Image Segmentation and Matching

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Abstract

A representation is described for two-dimensional anatomic shapes which can be described by single-valued distortions of a circle. The representation, called a radial contour model, is both *generic*, in that it captures the expected shape as well as the range of variation for an anatomic shape class, and *flexible*, in that the model can deform to fit an individual instance of the shape class. The model is implemented in a program called SCANNER (version 0.61) for 2-D interactive image segmentation and matching. An initial evaluation was performed using 7 shape models learned from a training set of 93 contours, and a control model containing no shape knowledge. Evaluation using 60 additional contours showed that in general the shape knowledge should reduce interactive segmentation time by a factor of two over the control, and that for specific shapes such as the eye, the improvement is much greater. A matching function was also devised which showed that the radial contour model should allow diagnosis of subtle shape changes. These results suggest that the use of spatial anatomic knowledge, when combined with good interactive tools, can help to alleviate the segmentation bottleneck in medical imaging. The models, when extended to more complex shapes, will form the spatial component of a knowledge base of anatomy that could have many uses in addition to image segmentation.

Introduction

Structural biology is a basic medical science that studies the physical organization of the body at levels ranging from gross anatomy to molecular biology. At the gross level, anatomy provides a framework upon which most of the basic as well as clinical sciences rest, and is therefore one of the most important courses taken by medical students. However, most anatomy and structural biology remains a qualitative discipline, and the study of anatomy has not changed appreciably over several hundred years. In recent years the rapid explosion of medical information of all kinds requires that computer-based methods be developed for managing and organizing this vast array of information. Because of its fundamental nature, anatomy and structural biology could provide a framework for organizing medical information so that it could be managed and utilized more effectively. However, in order to do this methods for representing anatomical knowledge in a computer must be found.

At the University of Washington we are engaged in a project called the "Digital Anatomist", one of whose long term goals is to develop methods for representing anatomic knowledge. In a recent paper we described a framework for developing a knowledge base of structural biology, and described two basic types of anatomic knowledge, symbolic and spatial [4]. Symbolic anatomic knowledge is knowledge contained within the text of an anatomy textbook, and includes the names of objects, their function, pathology, etc. Our progress towards representing this type of knowledge is described elsewhere [7].

Spatial anatomic knowledge, on the other hand, is traditionally learned from images, and determines the shape and range of variation of anatomic objects, as well as their relative geometric relationships. It is spatial anatomic knowledge that allows radiologists to interpret images, surgeons to plan operations, or oncologists to plan radiation treatment for cancer.

In particular, image interpretation requires that anatomic objects first be segmented from the image, after which they may be classified as normal or abnormal, either according to shape or other features. Although many attempts have been made to automatically segment medical images, none have been completely successful, with the result that most segmentation is still done manually. The major hypothesis of our approach to this problem is that spatial knowledge of anatomy is necessary in order to interpret medical images, which is one of the main reasons that successful segmentation systems do not currently exist.

In this paper I describe our progress towards representing spatial knowledge of anatomy, and describe an implementation of this representation in an interactive program called SCANNER (version 0.61) which demonstrates the utility of spatial knowledge of anatomy for interactive image segmentation and matching. The short term goal of the program is not to completely automate segmentation, but to use knowledge to speed up the process.

Representation of Anatomic Shape

Our approach to segmentation is an example of model-based vision, in which models of the expected objects are either matched against regions in the image, or are used to guide the image analysis procedure [6] [8] [10].

The problem of developing computer models of anatomic shape is perhaps more difficult than that of devel-

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oping models of man-made objects in other model-based vision applications. The main added difficulty is biologic variation, that is, how to represent not only the expected shape of an object such as the kidney, but also the range of normal variation.

In our current research spatial knowledge is represented in a model that is *flexible* enough to accurately fit the data, but which also is *generic* in that it captures the expected shape of an anatomic shape class as well as its range of variation. The ability to explicitly encode variation in a flexible, generic model allows a model-based system to predict search regions on the image, while at the same time providing an accurate fit of the model to the data.

The model employed in SCANNER is called a radial contour model (RCM). This model is an example of a geometric constraint network, a type of constraint network [9] which has been proposed as a general representation for biologic objects [3]. The hypothesis behind this representation is that networks of local interacting geometric constraints between structure subparts, when interacting together, are able to generate an overall representation of the essential shape and range of variation of the structure. The RCM is a 2-D implementation of a previously reported 3-D representation that was used in a knowledge-based 3-D ultrasonic organ modelling system [2]. However, the previous representation was not implemented in an interactive system, nor was it ever tested on clinical images.

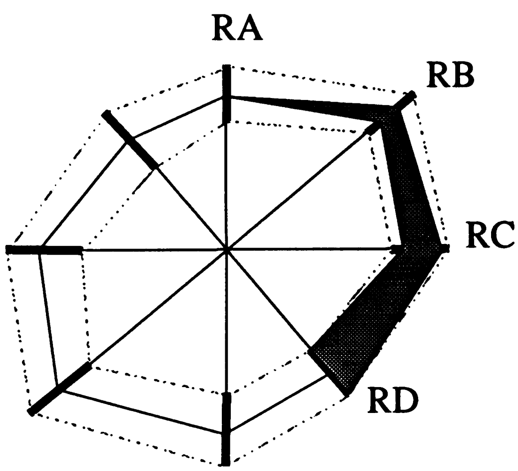

Figure 1. Radial contour model

Figure 1 shows the radial contour model, which can be used to represent 2-D contours that are single-valued distortions of a circle. A general constraint network consists of a set of variables, a set of possible values for each variable, and a set of constraints that determine which of the possible values for the variables are compatible [9]. In the case of the radial contour model the variables are points on the contour boundary, each of which is restricted to lie along a set of fixed radials emanating from a local contour coordinate system. The value for a single variable is the distance from the origin to the contour boundary, and the possible values are given by one-dimensional *uncertainty intervals* along each radial (shown as darkened lines). Lines drawn between the inner endpoints of each interval, and between the outer endpoints, define a 2-D search region within which the computer always expects the contour on the image to lie. Lines drawn between the midpoints of all the intervals defines a contour which represents the best guess at any one time as to the actual location of the contour in the image.

Constraints between radials are defined from a training set of similarly shaped contours. In a local radial contour model, each radial is only constrained by its nearest physical neighbor, whereas in a maximal radial contour model every radial is constrained by every other radial. For each member of the training set, and for each pair of radials RA and RB connected by a constraint, the ratio is measured between the observed distance along RA to the contour and the observed distance along RB to the contour. The range of such observed ratios defines the constraint between RA and RB. That is, if the value of RA is given (say by an edge in the image) then the constraint states that RB must be within an interval given by the constraint.

These constraints interact with image data by a constraint propagation process, which is shown as the shaded area in figure 1. An edge or user input for radial RA causes the uncertainty interval for RA to be reduced to a single point (the possible values for RA in the constraint network now consist of only one point, the edge observed in the image). This edge information, when combined with the ratio constraint between RA and RB, propagates to RB, causing the uncertainty interval at RB to be narrowed from its original value. Although the interval is wider than at RA, the combination of knowledge of shape variation encoded by the constraint, together with measured data at RA, allows additional information to be inferred at RB. Since RB is now changed, its value can be propagated further to RC, and so on until an interval does not change, in which case the propagation wave stops (in this case, at radial RD). The result of this constraint propagation procedure is that edge information obtained in one part of the contour is able to reduce the search region for edges obtained in another part of the contour. This procedure is an application of relaxation labelling [9] [11] to the problem of model based segmentation. Details of the procedure may be found in the previous report [2], along with a proof that, under a

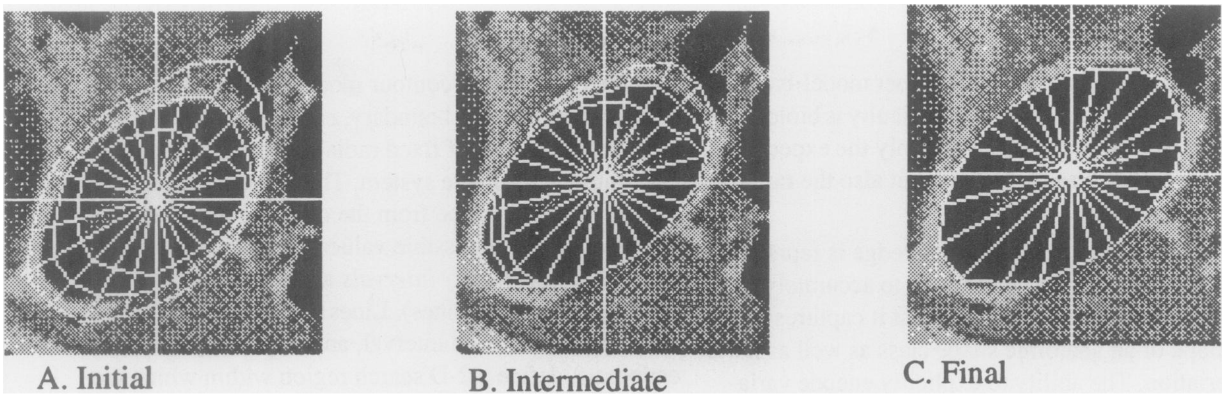

Figure 2. Model-based segmentation of the kidney

reasonable assumption, the procedure executes in O(N) time.

The SCANNER Program

The radial contour model has been implemented in a program called SCANNER (version 0.61) in order to demonstrate and evaluate the utility of the radial contour model for interactive 2-D image segmentation. SCANNER is implemented in Objective-C on the NeXT computer, and makes extensive use of the interface development tools available on the NeXT. Additional details of the SCANNER user interface are described elsewhere [5].

In order to perform interactive segmentation and matching, the user provides the name of a previously created radial contour model representing the expected shape and range of variation of a set of similarly shaped contours. Figure 2 shows three stages in the interactive segmentation of the kidney from a cross-sectional CT image, utilizing the maximal radial contour model. Initially, an initial radial contour model appears in the center of the image, after which the user positions the mouse to move the center of the radial contour to the perceived center of the object on the image. This operation bypasses the problem of locating a frame of reference for the local coordinate system, which is an example of the matching problem that is not likely to be solved in the near future. Although this problem is difficult for the computer, it is not difficult or tedious for the user. The approach to this problem taken in SCANNER is typical of the approach to the segmentation problem in this research: let the user continue to perform the tasks that are difficult for the computer, but let the computer perform those tasks it can do, and which will result in an overall speedup in the segmentation time. As further research improves the model-based approach, more of the tasks can be transferred to the computer, thereby gradually iterating towards a completely automated system.

Once the user has moved the center of the contour to the center of the object on the image, he or she indicates the position of the contour along a single radial, and constraint propagation causes the search region to be narrowed from its initial value. In Figure 2A the user has indicated the position of the contour along the positive X-axis, and constraint propagation has created the initial search region. The computer then sequentially chooses a radial (currently the radial with the smallest uncertainty), sends the line of pixels corresponding to the uncertainty interval along the chosen radial to a one-dimensional edge finder, and uses the returned edge to initiate the constraint propagation procedure. Figure 2B shows the model after several radials have been found. The search terminates when all the radials have been examined (figure 2C). If the computer incorrectly finds an edge the user can manually correct the offending radial.

Once the corrected contour has been found it may be matched against any number of other radial contour models, in order to determine the shape class to which the contour is most similar. The matching function between a given contour and a candidate model is defined as follows: For each constraint in the model the ratio between the corresponding pair of radials in the contour is determined. If this ratio is within the limits defined by the constraint then 0 is added to the match score. Otherwise the squared distance between the measured ratio and the closest endpoint of the constraint interval is added. Thus, if a contour satisfies all the constraints in the model then the match score is zero, whereas the magnitude of a non-zero score is taken to be a measure of the degree of dissimilarity between the shape class encompassed by the model and the particular shape defined by the contour. The model with minimum match score is taken to be the model whose shape is most similar to the contour.

Initial Evaluation

An initial evaluation was performed to determine how useful the addition of learned shape knowledge might be for semi-automatic 2-D segmentation and matching. For this purpose, a series of 2-D medical images were obtained, radial contour models were built for several structures, and measures of usefulness and matching were devised.

Models and training sets

The models were generally created from slices at different levels in one or more patients or cadavers. Each model encoded in the constraints the shape and range of variation of several cross-sections of the object given as a training set. In addition to these models, a control model was created which contained very wide constraint limits, thus allowing a comparison to be made between the same segmentation procedure using no knowledge, and the segmentation procedure using specific knowledge of shape contained in the learned models.

Test procedure

A special module was written for SCANNER which allowed a test set of images to be created and evaluated for several model types. The test set consisted of 60 contours of the 7 objects described by the models, 3 contours for each of 20 image slices from the same patients and cadavers that were used to create the models, but from slices that were not included in the training set. For each of the test contours the origin and one point were specified by the user. This initialized set of 60 contours was then automatically segmented using both the learned shape models and the control model, thus ensuring that the same initial conditions applied to both the control case and the case using knowledge. For both the control and the knowledge case, once the segmentation had been completely performed the user examined each of the 60 contours and corrected any radials that were not on the perceived contour boundary in the images. The number of such corrections was recorded for each contour as a measure of usefulness. That is, if the user has to correct all 23 radials (the number of radials in the test models) then the model is not useful, since it is no better than completely manual segmentation, whereas if the user does not have to correct any radials then the system is as useful as it can be given its interactive nature.

Once each contour had been corrected by the user, the corrected contour was matched against each of the 7 generic models, and the model with lowest match score was taken to be the model to which the contour was most similar. Match scores against the other models were recorded as well.

Test results

Model	N	Knowledge	Control
Cortex	6	3.3(2.6)	23.0(0)
Carotid	3	8.7(5.7)	15.3(1.2)
Eye	12	2.9(6.7)	17.1(3.7)
Thorax	12	17.9(2.2)	23.0(0)
Kidney	12	4.4(5.1)	18.7(2.6)
Liver	12	11.8(5.1)	22.4(1.2)
Brainvent	3	10.0(1.7)	2.0(1)
Totals	60	8.7(7.3)	19.4(5.2)

Table 1. Usefulness of knowledge for segmentation

Table 1 quantifies the usefulness of shape knowledge in this situation. For each model the number N of test contours is shown. Since there were 3 test contours per test slice, the number of test slices is just the number of test contours divided by 3. The 2nd to last column shows the mean and SD of the number of user corrections that had to be made when the learned shape model was used for segmentation, and the last column shows the number of user corrections that were made when the control model was used. The overall means and SD's for the control and knowledge models are shown in the last row of the table. All differences were significant at $p < .01$, except in the case of the carotid.

For the match test, in all but one case the contour matched the expected model, and in that case a contour from the eye matched the carotid model, which is almost a circle on cross-section.

Discussion

On average the addition of specific shape knowledge increased the usefulness of the segmentation by a factor of two (19.4 to 8.7) where all other factors except the addition of shape knowledge had been factored out by the nature of the test. The general reason for the increased usefulness was the smaller search regions provided by the shape knowledge. For specific models the increase was more, with the eye being the most useful (an increase of a factor of 6, as might be expected since the variability in the eye model was small). In general the usefulness increased with decreased variability in the model, but there were not enough samples in this preliminary evaluation to show this relationship conclusively.

In one case the shape model did more poorly than the control model. The difficulty in the case of the *brainvent* model was that, with only 3 training slices the search region specified by the learned model was exterior to the actual contour on the test case, and since the first edge found by the edge finder happened to be the correct one, the control model did better. This situation should be alleviated by adding more training examples, so that the model search region encompasses more instances of the shape.

The match results show that the constraint model appears to allow fairly subtle discrimination between shapes since many of the shape models were similar. If these results generalize, then the radial contour model (and by extension, the more general geometric constraint network model) may prove very useful for classification of subtle abnormal shape changes, as well as matching of regions found by low level image processing functions to shape models. This latter capability should lead towards the development of more automated segmentation programs.

Conclusions

This paper has described our progress towards a representation for spatial anatomic knowledge that is both flexible in that it can match specific organ instances, and generic, in that it captures the expected shape and range of variation for a class of anatomic shapes. Although the current representation, the radial contour model, cannot describe all anatomic objects, it should be adequate for many clinical situations such as radiation treatment planning, or cardiac wall motion analysis. The representation has been implemented in a program for semi-automatic knowledge-based segmentation and matching. Although greater numbers of patients are needed, the initial results suggest that, even in the absence of more sophisticated low level image processing, the shape model can reduce the segmentation time by at least a factor of two, and can be useful for shape classification for diagnosis and automated image analysis. When these capabilities are combined with good interactive tools, more sophisticated knowledge-based low level image processing techniques, and more general geometric constraint network representations, the possibility exists for greatly alleviating the segmentation bottleneck that is one of the major reasons why image analysis is not more widely used in clinical medicine. The models should also have applicability as the foundation for a spatial knowledge base of anatomy, which, because of the fundamental nature of anatomy and structural biology, should find widespread use for many applications.

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