Model based segmentation of medical x-ray images

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ABSTRACT

This paper discusses the methods used to model the structure of x-ray images of the human body and the individual organs within the body. A generic model of a region is built up from x-ray images to aid in automatic segmentation. By using the ribs from a chest x-ray image as an example, it will be shown how models of the different organs can be generated. The generic model of the chest region is built up by using *a priori* knowledge of the physical structure of the human body. The boundaries of the different organs can be found by using this information in an intelligent manner. The models of the individual organs are built up by using knowledge of the structure of the organs as well as other information contained within each image. Each image is unique and therefore information from the region surrounding the organs in the image has to be taken into account when adapting the generic model to individual images. Results showing the application of these techniques to x-ray images of the chest region, the labelling of individual organs and the generation of models of the ribs will be presented.

1 INTRODUCTION

One of the problems associated with the enhancement of x-ray images of the chest region for diagnostic purposes is the different exposure levels of the different organs.[1,2] Applying one enhancement technique to the entire image causes some areas to be enhanced effectively while in other regions image quality is reduced. There is thus a requirement to be able to apply different enhancement techniques to different regions within an x-ray image of the chest. If models of these different regions and organs are available we can use the theoretical model to aid in the further enhancement of the image.

To be able to do this, it is first necessary to identify the different regions of interest. In this paper we discuss the use of *a priori* knowledge that is available about the structure of the human body to implement this segmentation process. We begin by describing a framework within which this knowledge based image processing can be implemented. Different levels of knowledge are defined and the relationships between these different levels are discussed. The use of object oriented methods in the design and implementation of such a system is proposed. The concepts presented here are not specific to medical imaging but can be generally applied to any image processing application. We go on to describe how these knowledge based techniques can be applied to the problem of segmenting x-ray images of the chest region into the different organs. We show how we use the *a priori* knowledge to design algorithms that can be used to segment the chest region into the different organs. As an example of how we can model different organs we describe the modelling of a rib. We present a theoretical model and show how the actual image data that is available is used to adapt the model.

2 A KNOWLEDGE BASED PROCESSING FRAMEWORK

Knowledge based image processing can be defined as: *the use of information that is available about a particular class of images in the design and implementation of image processing algorithms that will be used on that class of images*. To make the best use of the information that is available it needs to be organized in such a way that the relationships and interdependencies between the different pieces of information are clearly defined.

2.1 INFORMATION AND IMAGES

Sakar and Boyer[3] propose the division of the information that is available to us about an image into four different levels: signal, primitive, structural, and assembly. These organizational levels are defined as follows for the case of a two dimensional image:

Signal: The organization of the raw signal that is being processed. This would involve the clustering of pixels into, for example, edge pixels and non-edge pixels.

Primitive: The organization of the features extracted from the raw signal. For example, edge pixels found in the signal stage would be joined to form the boundaries of regions in the image.

Structural: The organization of the primitive level features into structures. Corner finding, object recognition, and shape analysis are some of the operations that would be appropriate for this level. The result would be that boundaries are attached to definite objects within the image, such as a lung or rib.

Assembly: At this level we are concerned with organizing the features found in the structural level into higher level objects that have meaning when related to the context of the image. As an example, if we know where the mediastinum is then it follows that there should be a lung on each side of it.

Each of these organizational levels is made up of two types of information: that which can be extracted from the image by suitable processing, and that which is known before any processing is done on the image. The information that is obtained from the image by suitable processing does not contain any knowledge about how to interpret the contents of the image. The *a priori* information is used to interpret the extracted information and give it meaning within the context of the entire image or class of images. This interpreted information is then used in the next level in the hierarchy. This is perhaps best described by an example. Applying an edge detector to an image provides us with information as to whether any given pixel is an edge pixel or not. It does not tell us anything about the relationships between the pixels. The *a priori* information that is known, is that edge pixels that lie next to each other form a boundary between different regions. At a higher level in the hierarchy we would consider the information that there is a boundary in the image to be the information that we have extracted from the image. The *a priori* information could be that two boundaries at right-angles form a corner.

2.2 IMPLEMENTATION AND OBJECT ORIENTATION

The design of an image processing system that utilizes the different levels of information described above in a coordinated manner is not just a simple task of defining a set of processes that are implemented in sequence. The processes that are implemented at a particular level will depend on the type of information that is required in the next level leading to a top-down approach to the design of the image processing system. At the same time, when the system is actually implemented a bottom-up approach is used because the information needed by each level is obtained from the level below.

The use of an object oriented design paradigm[4] could provide a solution to this design and implementation problem. We can consider each piece of information that we have to be an object. The relationships between the different pieces of information can also be considered to be objects. The object oriented paradigm provides tools (classes and inheritance) that make it easier to describe the relationships between different objects and the different processes (methods) that can be applied to each class. The effective implementation of a knowledge based system using object oriented principles will be reliant on the definition of the initial classes of information.

3 KNOWLEDGE BASED SEGMENTATION OF THE CHEST REGION

Our aim here is to use the *a priori* information that we have about the structure of the chest region to define models that will aid us in the automatic segmentation of x-ray images of the chest into the different organs that are present. These would include lungs, ribs and the mediastinum. Figure 1 shows an example of a typical chest x-ray.

Figure 1: Typical x-ray image of the chest region

By studying several such images we can extract information about the structure of the chest region that is invariant across images. This is a very important step in the modelling process. It is only necessary to extract the information that will be of benefit to the processing that will be done on the image. To define a model that we can use to implement segmentation of a chest x-ray, we need to find the information that defines the differences between regions. We also take into account the physical structure of the image. The following is information that can be extracted from a typical x-ray image:

1. The lungs appear darker on an x-ray image than the surrounding area and the mediastinum.
2. The mediastinum will always be vertical and run along the middle of the x-ray.
3. The heart protrudes from the mediastinum on the right hand side when looking at the x-ray from the direction in which the x-ray beams travelled.
4. The ribs are approximately horizontal and span out from the mediastinum through the lungs to the outer edge of the chest.

We use this information to construct algorithms that can be used to implement the segmentation process.

3.1 LUNG SEGMENTATION

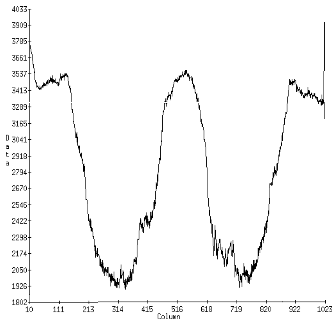


Figure 2: Horizontal cross section through the chest

The first piece of information that we know is that the lung region is darker than the rest of the image. This immediately suggests some sort of threshold process. Figure 2 shows the profile of a horizontal cut through the x-ray image of the chest. Sherrier and Johnson[2] show that the intensity levels spanned by the pixels in the lung region cover approximately the lower two thirds of the full range of pixel values. We use this information to find the threshold level used to perform the segmentation. We could also have used the histogram threshold method described by Sezan et al.[1] The following describes the algorithm used to implement this process:

1. For each row in the image, find the peak in the middle of the row. This peak will occur in the mediastinum.
2. Take the average of these peaks.
3. Find the lowest pixel value in the image.
4. Find the value that falls two thirds of the way between the lowest value and the average of all the peaks.
5. Use this value as the threshold value.
6. Threshold the image to obtain a binary image with the mediastinum represented by 1's and the lungs by zeros.
7. Perform a morphological erosion followed by a dilation to break off any small jutting pieces.
8. Discard all small regions (less than 10000 pixels in size).
9. Use this mask image to extract the two different regions that have been segmented.

Figure 3 shows the thresholded image. We use this thresholded image to extract the lung region from the original image.

3.2 RIB SEGMENTATION

We can summarize the information that we know about the ribs as follows:

1. They will be found in the lung region of the segmented image.

Figure 3: Thresholded chest image

2. They stretch across the entire width of the lung region.
3. They are oriented in a horizontal direction.
4. The edges are smooth and have no sharp changes in direction.
5. They are evenly spaced.

We use this information to design an algorithm that will find the edges of the ribs. The following is a description of the process used:

-1	-2	-1
0	0	0
1	2	1

(a) Sobel

0	0	0
1	1	1
0	0	0

(b) Morphological

Figure 4: Kernels used for edge enhancement

1. Find the gradient of the edges in the image that run in a horizontal direction. We convolve the image with one of the Sobel edge kernels. This kernel is shown in figure 4(a)
2. Use an edge detection algorithm to find all the edges in the image. We use the *first derivative operator for symmetrical exponential filter*.[5] This finds all edges, both horizontal and vertical.
3. Remove all the vertical edges from this edge detected image. We use binary morphology. An erosion followed by a dilation with the kernel shown in figure 4(b) are performed.
4. Use the gradient and edge images as inputs to an edge closing routine.

The results of applying the above algorithm to the right lung are shown in figure 5. Further edge closing that utilizes more of the *a priori* information will need to be done on this image.

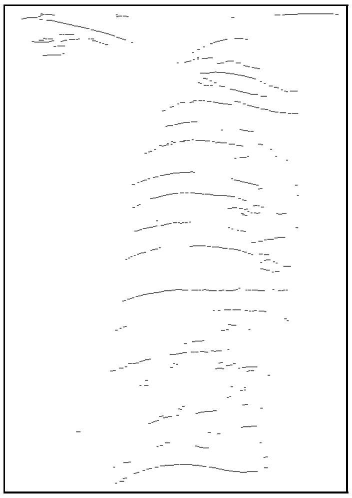


Figure 5: Image of the right lung after horizontal edge detection and edge closing

4 MODELLING OF THE ORGANS

The image formed on an x-ray film is a function of the x-ray energy incident on the film. The x-ray energy I transmitted through a material is defined by Lambert-Beer's Law[6]

$$I(x, y) = I_0 e^{-\mu \rho z} \tag{1}$$

where I_0 is the incident x-ray energy and μ is the x-ray attenuation coefficient, ρ the density and z the thickness of the material through which the x-ray beam passes.

Due to the exponential nature of equation 1 the energy transmitted through an organ is also function of the other organs that the x-ray beam passes through. We can transform this multiplicative attenuation to additive attenuation by taking the logarithm of each pixel in the image.[7]

The measure of x-ray film blackening is the density:

$$D = \gamma log_{10} \left(\frac{L_0}{L} \right) \tag{2}$$

where L_0 and L are the incident and transmitted light intensities respectively and γ is a property of the x-ray film. Exposure is the same as received x-ray energy I so we can write:

$$D = \gamma log_{10} \left(I_0 e^{-\mu \rho z} \right) \tag{3}$$

Combining equations 2 and 3 and dropping the logarithms, we can write

$$\frac{L_0}{L} = I_0^{\gamma} e^{-\mu \rho z} \tag{4}$$

L is the transmitted light through the film and is the data which is digitized. Rearranging the above and taking natural logarithms produces

$$\ln(L) = \ln\left(L_0 I_0^{-} \gamma\right) + \mu\rho\gamma z \tag{5}$$

Therefore, by taking the natural logarithm of the digitized x-ray, we have an image where the intensity level of each pixel is proportional to the attenuation. For multiple organs in the path of an x-ray, the image intensity is proportional to the sum of the different attenuation factors. This implies that if we know the attenuation factor of an organ, we can subtract the effect of that organ from the image without altering the effects caused by other organs in the x-ray beam path. We show how we can do this by constructing a simple model of a rib and then subtracting that model from the image.

4.1 Modelling the image of a rib

We can approximate the shape of a rib as a cylinder. In x-ray images of the chest, the x-ray beams travel through the rib as shown in figure 6.

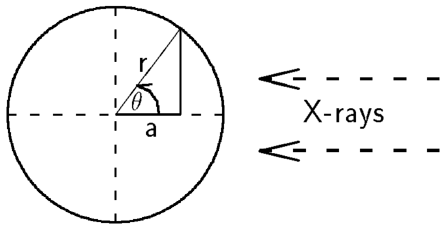


Figure 6: Cross-section of modelled rib showing the x-ray path

The path length z that the x-ray beam travels through the rib is given by

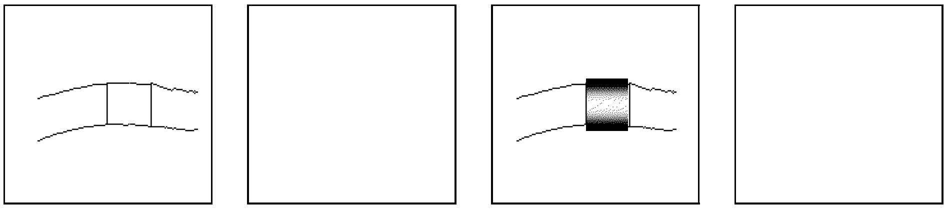
$$z = 2a = 2r\cos(\theta) \tag{6}$$

and inserting this into equation 5, we get

$$\ln(L) = \ln\left(L_0 I_0^{-} \gamma\right) + 2\mu\rho\gamma r\cos(\theta) \tag{7}$$

We can approximate the first term $\ln\left(L_0 I_0^{-} \gamma\right)$ as the average background value surrounding the rib in the x-ray image. Subtracting this average value from the image of the rib will leave us with the representation of the x-ray energy transmitted through the rib $\mu\rho\gamma r\cos(\theta)$. Using the image containing the edge detected ribs, we can measure the length of r in pixels. At the center of the rib $\cos\theta = 1$ and we can thus get an approximation for the $\mu\rho\gamma$ term by measuring the intensity levels along the center line of the rib. This enables us to create the image representation that a perfectly cylindrical rib would have given.

Figure 7 shows the results of modelling a section of a rib. Figure 7(a) shows the edge detected rib with the area that we will model between the two vertical lines. Figure 7(b) shows the original rib, figure 7(c) shows the projected image of the model created for the middle section of that rib and figure 7(d) shows the results of subtracting the model from the original image. These results show that even with a very basic model such as the one that we have used, the image created by the rib has been subtracted out leaving the rest of the image intact.



(a) Edge detected rib showing area of interest

(b) Original image of rib

(c) Model of area of interest

(d) Rib with model subtracted

Figure 7: The modelling of a piece of the rib

5 CONCLUSION

We have described a framework for the implementation of knowledge based image processing and proposed an object oriented paradigm for the implementation of such a framework. By applying some of these principles to the segmentation of x-ray images we have shown that theses techniques can be used effectively in the design and implementation of image processing algorithms. We have also shown, using a simple model, how we can model the x-ray images that individual organs produce. The model is adapted to fit the data contained in the image and then subtracted from the image enhancing detail that would otherwise have been obscured by that organ.

6 ACKNOWLEDGEMENTS

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7 REFERENCES

[1] M. I. Sezan, A. M. Tekalp, and R. Schaetzing, "Automatic anatomically selective image enhancement in digital chest radiography," *IEEE Transactions on Medical Imaging*, vol. 8, pp. 154–162, June 1989.

[2] R. A. Sherrier and G. Johnson, "Regionally adaptive histogram equalization of the chest," *IEEE Transactions on Medical Imaging*, vol. MI-6, pp. 1–7, Mar. 1987.

[3] S. Sakar and K. L. Boyer, "Perceptual organization in computer vision: A review and a proposal for a classificatory structure," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, pp. 382–399, Mar. 1993.

[4] S. Khoshafian and R. Abnous, *Object Orientation.* John Wiley and Sons, Inc, 1990.

[5] University of New Mexico, *KHOROS Manual.* Entry for the "vgef" program.

[6] B. Jacobson and J. G. Webster, *Medicine and Clinical Engineering.* Prentice-Hall, Inc, 1977. Chapter 8 - Diagnostic Radiology.

[7] W. Borchardt, "Computer-assisted detection of lung cancer nodules in medical chest x-rays," Master's thesis, Department of Electrical Engineering, University of Cape Town, South Africa, 1992.