Ultrasound Image Segmentation and Compression

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1. INTRODUCTION

Ultrasound imaging has proved to be an exceedingly ubiquitous imaging modality in the field of diagnostic medicine. The need for maintaining archival databases of ultrasound images for patient follow-up as well as research applications, coupled with the existence of limited storage capacities, has prompted the search for efficient compression schemes for the same. Compression is also warranted in situations, where one is interested in creating a major, shared database of diagnosed images, for the purpose of physician training in ultrasound interpretation.

In general, the ultrasound images have two distinct regions:

- The area under the sector which gives the diagnostically useful echo information
- The annotations comprising the textual data about the patient name, ID, name of the scanning centre, date, time, etc.

The sector has wide gray-scale variations while the background with the annotations possesses essentially binary information. Effective compression cannot be achieved by the application of a single compression scheme on these two distinct areas of significance. Thus, initially, the image needs to be segmented into the two regions and then appropriate compression schemes need to be applied. In this paper, we present a novel way of segmenting the image using a combination of edge detection and boundary extraction techniques. Subsequently, we discuss the application of compression algorithms on the segmented regions.

2. METHODS

2.1. Edge Detection

Boundaries of objects in an image are normally areas of intensity discontinuities. When the boundaries are discontinuous, and/or not distinct, as is normally the case, designing algorithms that find the boundaries of objects directly from the gray level values in the image is difficult. The solution to this lies in first transforming the image into an intermediate image of local gray level discontinuities, or edges and then connecting these into a closed contour. Thus the edge detection operation tends to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries.

An edge operator is a mathematical operation with a small spatial extent designed to detect the occurrence of a local edge in the image function. All useful edge operators compute the gradient, with a direction that is aligned with the direction of maximal gray level change and a magnitude describing the severity of this change. The most widely used gradient operators are Roberts, Sobel, Kirsch, Previtt and Laplacian.

2.2. Boundary Extraction

Because of the nature and SNR of the ultrasound image, one gets only unconnected edge elements. Additional processing needs to be done to group edge elements into structures better suited to the process of interpretation. The goal of segmentation is to make a coherent, connected edge contour from many local individual edge elements. The boundary extraction is a grouping operation that maps the edge elements into boundaries.

The Hough transform is a versatile, global technique to extract boundaries that can be described analytically such as straight lines, parabolas, circles and other curves that can be specified by a small number of parameters [1]. In Hough transform, the basic concept is to obtain the locus, in the parameter space, of the set of curves passing through each candidate edge element in the given image. The nature of the curve looked for is pre-defined, depending upon the expected shape of the edge contour. The parameter space is quantized into cells, and an accumulator assigned to each cell. The content of the accumulator of every cell subtended by each locus is incremented by 1. The accumulator cell with the largest resulting contents determines the existence and the location of the most likely curves from the specified class, in the given image. It is, thus, the intersection point of all the loci, corresponding to a particular edge curve.

2.3. Compression

Image compression is the science of coding digital images to reduce the number of bits required in representing an image while providing the level of quality and intelligibility required for the given application. Lossy image compression techniques concede a certain loss of accuracy in exchange for greatly increased compression. However, this loss of accuracy may not always be visually apparent and can be controlled by suitable design. Lossless image compression produces an exact duplicate of the image after a compress/reconstruct cycle, but yields a very low compression ratio.

In vector quantization [2], a lossy compression technique, a function – the quantizer is used to map all possible input vector values into a smaller number of output vectors. In this way, the number of symbols that need to be encoded are reduced, at the expense of introducing error in the reconstructed image. A *k*-dimensional vector, $X = [x_1, x_2 \ldots\ldots x_k]$, whose components represent the discrete or continuous signal sample values, is mapped or quantized into one of N possible reconstruction vectors Y_i, $i = 1,2,3\ldots N$. The distortion in approximating into one of N possible reconstruction vectors Y_i is denoted by $d(X,Y_i)$ and is defined according to the application. The most common distortion measure is the Mean Square Error (Euclidean distance). The set Y is referred to as the reconstruction codebook and its members are called code vectors [3]. The codebook design problem is to find the optimal codebook for the given input signal statistics, distortion measure, and codebook size N. Once the codebook has been determined, a given input vector is compared to all the entries in the codebook and is quantized to the code vector that results in the smallest distortion [4].

Run Length coding is a lossless compression scheme that exploits the spatial redundancies in an image. For a one-dimensional run length coding, a run length is defined as the number of successive pixel elements having the same value. The image can be coded using the pair: (runlength, gray code).

2. RESULTS

Patient scans were recorded in videotapes at Mediscan Systems, Chennai. The ultrasound images were digitized from these videotapes using a Creative™ frame grabber card. The images were preprocessed using a variety of filters. Suitable low pass filters were used to blur out unwanted edges while the high pass filters were used to enhance useful edges around the sector. The local edges around the sector were detected using various edge operators described earlier, with Sobel operator providing the best results. During boundary extraction, the area of search for the lines and the arcs in the image plane was restricted. A suitable range was chosen for the parameters (angle and the vertical distance for the lines, and the origin co-ordinates and the radius for the arcs). The equation of the straight lines and arcs, deduced from the implementation of the Hough transform algorithm, were found to represent the sector boundaries effectively within the limits of digitization.

Since the region surrounding the ultrasound sector area contains predominantly text, it was converted into a binary image by choosing an appropriate threshold. During run length encoding, only the level of the first pixel in the binary image was stored as the starting point for the encoded run lengths. Vector quantization requires the image to be transformed into vectors. Since the sector under consideration is not a regular polygon, innovative schemes were devised to derive the maximum number of square blocks of size 4 X 4 (representing a 16-dimensional vector) from this region. A set of 10 training images were selected and the codebook was formed by using these images simultaneously. The codebook was formed as per the popular LBG algorithm [5] and a codebook size of 512 was found to be adequate. Fig. 4 shows the reconstructed image, obtained after the above mentioned compression scheme. The original image is shown in Fig. 3. Fig. 1 shows the output after the edge detection operation, and Fig. 2 shows the actual gray scale sector area, segmented using the Hough transform. The compression ratio obtained with run length coding was 18.38:1, while that for vector quantization was 14.22:1, entailing a total compression ratio of 15.35:1. The PSNR was found to be 36.46 dB while the RMSE was 3.83.

3. DISCUSSION

Most of the ultrasound images used had sectors with faint boundaries and this made the sector information appear to merge with the background. Thus, depending on the quality of the image, various preprocessing tools such as filters and edge operators were used till a satisfactory edge image was obtained, as a prelude to segmentation. However, in general, Sobel edge operator proved to be effective when used in conjunction with a high pass filter. The Hough transform algorithm was found to be a sensitive algorithm with the likelihood of false maxima in the parameter space as a function of noise. Hence, restricting the area of search and selection of suitable range of parameters proved to be highly efficient in detecting the lines and the arcs with a great degree of accuracy. Though a certain amount of qualitative loss was introduced due to thresholding, the textual data was readable. In vector quantization, the method of forming the codebook from 10 diverse images simultaneously, was found to be more satisfactory than the conventional method, as it reflected the contents of all the images rather than the latest training image. Analysis of reconstructed images showed that codebook sizes of less than 512 accentuated distortion, while larger codebook sizes compromised on the computational speed.

4. CONCLUSION

The ultrasound images were effectively segmented and compressed by implementing the techniques described in this paper. The fidelity of the reconstructed images was found to be satisfactory, from the clinical point of view.

5. REFERENCES

[1] Sklansky, J., 1978: “On the Hough Transform for Curve Detection“, IEEE Transactions on Computers, pp. 923 – 926.

[2] Gray, R., 1984: “Vector Quantization“, IEEE ASSP Magazine, pp. 4 –28.

[3] Buzo, A., Gray, A., Gray, R., Markel, J., 1980: “Speech coding based upon Vector Quantization“, IEEE Transactions on Acoustics, Speech and Signal Processing, pp. 562 –574.

[4] Gersho, R., Cuperman, V., 1988: “Vector Quantization : A Pattern Matching Technique for Speech Coding“, IEEE Communications Magazine, pp. 15 – 20.

[5] Linde, Y., Buzo, A., Gray, R., 1980: “An algorithm for Vector Quantization Design”, IEEE Transactions on Communications, pp. 84 – 94.

Fig. 1. Edge Detected Ultrasound Image using Sobel operator.

Fig. 2. Ultrasound Image Segmented using Hough Transform.

Fig 3. Original Ultrasound Image

Fig 4. Reconstructed Ultrasound Image