Separation of Heart Wall in Echocardiograms by Supervised Image Segmentation*

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Abstract

Image segmentation is a process of dividing an image into meaningful regions. Human supervision of computer generated segmentation is essential for the tasks such as medical image analysis, surveillance-radar image analysis, etc. The decisions to be made based on the segmented images is often critical in such domains, and neither human imprecision nor the unreliability of automatic algorithms is tolerable. We develop a collaborative scheme that facilitates active human supervision of computer segmentation of images. Through this, we complement the reliability of a human expert with the precision of segmentation and deformable modeling algorithms that track a stationary or moving nonrigid object in a sequence of snap-shots of the scene.

In our system, an expert user observes the computer generated segmentaion along with the original images in a user friendly graphics environment, and interactively indicates the wrongly classified regions either by *pointing* or by *circling.* The precise boundaries of indicated regions are computed by studying original image properties at that region, and the human visual *attention distribution map* obtained from the published psychological and psychophysical research. All refinement operations are defined in the form of a linear functions so that the facilities such as error recovery, commutativity of operations, etc. are inherent to the system.

We use the developed theory to extract heart walls from a sequence of two dimensional echocardiograms. Echocardiography is one of the most popular and safest methods of observing the heart. Segmentation of the heart wall in echocardiograms is essential to detect and quantize a large spectrum of heart abnormalities.

1 Introduction

Image segmentation and nonrigid motion tracking have been two important problem domains in computer vision [1, 2, 3, 4, 5]. Our research facilitates reliable segmentation of

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a moving flexible object, from a sequence of images, through visual supervision and active interaction. The main contributions of this research will be in laying the foundations of human collaboration with region growing and deformable modeling algorithms using the human visual attention distribution model obtained from the published psychophysical research [6, 7, 8].

1.1 Need for Expert Supervision

Image segmentation in general, is a highly domain dependent task of dividing an image into meaningful regions. It is being widely used in many fields where spatial data of a scene to be analyzed is obtained. Success of a segmentation algorithm is usually assessed by the accuracy of its approximation and the fraction of the domain that it can correctly classify. Completely automated image segmentaion systems have been used satisfactorily in the fields where the decisions made through computed results are not very critical or where a specified error rate is acceptable. For example, the applications such as automatic sorting of mail [9, 10], barcode reading in supermarkets[11] have been shown to benefit from automated decision making. On the other hand a method with a low error rate may not be acceptable if the computed results were to be used to decide the exact contours of the brain tumor to be destroyed or if the heart wall contours generated by the computer were to be used to decide whether to carry out an open heart surgery.

Currently, such critical decision making is usually handled by human experts. Although human experts are good at classifying the regions of interest in a global sense, they are imprecise at drawing detailed boundaries of the regions. Such jobs are either very tedious or the required precision may be beyond human capability [12]. Hence the manually traced region boundaries are often not reproducible and may contain subjective local variations. In addition, even though an expert can provide a good qualitative assessment of the observed data, it is difficult for him to provide precise quantitative results [13]. In the field of medicine, experts seek quantitative results not only for diagnosis and surgery, but also for proper patient follow-up and expert consultations [14].

Experts in these specialized fields use extensive domain knowledge acquired over the years to do proper segmentation. If a computer were to be used for automated segmentation, to get reliable segmentation, one should encode extensive, often complicated domain knowledge, along with developing efficient and reliable inferencing and information retrieval mechanisms. The drive in our research is to avoid this costly process by using expert inputs when necessary.

The aim of our research is to facilitate collaboration between an expert adviser and the relevant segmentation algorithms, so that the collaborated output exhibits the reliability of the expert, and reproducibility and precision of the computer algorithms. This will facilitate active participation of human experts in the critical decision making systems that are based on image segmentation in general. This research yields new segmentation and deformable modeling algorithms to collaboratively refine the image segmentation generated automatically.

Overview of our supervised image segmentation scheme

1.2 Overview

Figure 1 shows an overview of our supervised image segmentation scheme, and a view of the display. We have developed a graphic package in the X-environment that allows an operator to view both the original and the processed image sequences side by side. It facilitates animation, forward and reverse scan, picking points or inputting contours, masking regions, binary expansion and contraction, changing the color maps and display constants, etc. All the available facilities are prompted in the form of a menu as shown in Figure 1B. The operations in the menu can be selected either by selecting them through a mouse click or through the keyboard.

Initially, a segmentation algorithms generates an estimate of the object to be segmented. The estimate is displayed along with the corresponding original image. The operator uses the visualization facility to compare the estimate with the original image. If any misclassified regions are found, he indicates them interactively either by pointing or by circling [15].

To enable natural interactions, we treat the interactive inputs as approximate suggestions, and not as accurate descriptions. In addition, to find the precise extent of indicated suggestions, we use human vision attention map obtained from psychophysical research [7]. Therefore all the interactive suggestions undergo refinement before execution. We have developed a region growing algorithm that finds the exact contours of the regions indicated by pointing, and a new deformable modeling algorithm that captures the exact contours of the circled regions. The developed algorithms automatically propagate the suggestions made on one time frame to other time frames, in case of a dynamic scene where a sequence of images is to be analyzed.

To enable effective supervision, in addition to natural gestures, *viz.* pointing and circling, we facilitate error recovery and commutativity of suggestions by defining each refinement action as a linear operation on the segmentation map generated during the initial segmentation. This enables iterative refinement. At any stage of corrections, if the updated estimate of the object is satisfactory, the supervisor can use it for direct quantitative measurements.

1.3 Previous work

1.3.1 Collaborative Updating

There has been little work on collaborative updating of the computer generated segmentations, but the need for such a scheme is emphasized by the number of interactive techniques that were proposed to overcome the difficulties of automatic processing of two dimensional echocardiographic data [48, 65, 66]. Adam *et al.* [48] initiated the segmentation by manually setting the border points of the object on a reference image. Angermann *et al.* [65] corrected the errors in the automatic segmentation by directly drawing the corrected contour on a reference frame, and then propagated it to all the frames by linear interpolation. A similar scheme was proposed by Zeiher *et al.* [66], where they manually corrected the computer generated estimates through an interfaced writing tablet.

The above methods require the interactively traced corrections be precise, and in many instances these corrections are propagated to other time frames by simple linear interpolation. This may lead to subjective variations and erroneous propagation of corrections, because heart wall motion is not known to be a linear function of time. To avoid this we developed a collaborative scheme where the computer is made to detect the precise boundaries of the suggested corrections [63]. In this scheme we generate an initial estimate of the heart wall by morphologically influenced thresholding, and refined the estimate by picking points on the misclassified regions. Pointing and circling are convenient modes of interactive specifications [67, 68, 69, 15, 70]. In addition, in case of poor quality data, when it is not easy to specify a region precisely, a user prefers circling to indicate fragmented regions [67]. We use both pointing and circling for refining the heart wall.

1.3.2 Human visual attention models

Simple actions such as pointing and circling are often imprecise and ambiguous. There have been attempts to study these imprecisions and disambiguate the gestures [71, 72]. A collaborative scheme must account for both the imprecision and the visual attention model, to make the corrections that match the expert's intentions.

An assumption central to the current view of visual expectancy effects is that the attention mechanism is limited in its spatial extent. It is usually characterized by the reaction time. A slower reaction time indicates an unexpected region and a faster reaction time indicates the attended region. Posner *et al.* [73] and Hoffman *et al.* [74] experimentally showed that there is a discrete bounded region around the point of attention, called the *spot-light*, with an uniform reaction time. The angle subtended by the spot-light is about 1^o at the viewer's eyes [75]. Later Ericsen [76] and LaBerge [77] showed that the spot-light has flexible boundaries and its size is task dependent.

Hughes *et al.* [6] examined the spatial extent of the visual attention by inducing subjects to expect the target at a location and introducing occasional probe flashes at other locations throughout the visual field. The main conclusion of their study was that the directed visual attention was not a spatially limited phenomenon, but it extended throughout the visual hemifield. It was independent of both the expected target locations and the validity of precue. In addition, they supported the spot-light theory by showing that the field of attention had uniform reaction time.

A psychophysical analysis of the visual attention span is reported by Mangun *et al.* [7], where they studied the changes in the event related brain potentials (ERPs) with respect to visual stimuli as the locus of attention was shifted across the visual fields. They observed a decline in attention indicated by decline in the amplitude of the sensory evoked components of the ERPs, at increasing distances away from the attended location. Their study supported both the spot-light and the gradient models of the visual attention maps. Additional evidences to support these models are provided by Shulman *et al.* [78] and Bashinski [79]. Tsal [80] showed that the decrease in attention was linear with respect to the angle subtended at the viewer's eyes.

While the above methods studied mainly the luminance detection paradigm, Downing [8] studied the visual attention maps for luminance detection, brightness discrimination and form discrimination paradigms. Her study revealed that visual sensitivity to these tasks was maximal where a target stimulus was expected and generally decreased with distance from that location.

We use these spot-light and gradient models of the visual attention maps in our collaborative refinement scheme.

2 Application: Extracting heart wall from two dimensional echocardiograms

Two dimensional echocardiograms are images of cross sections of a heart, obtained by methodic registering of the echoes generated by sound beam scans. The intensity of sound echoes are dependent on the type of the tissue, and change in the tissue type, at the point of backscatter. Echocardiograms record high intensity echoes at the points that correspond to the heart walls, valves and other tissue changes that lie within the scanning range. Two examples of echocardiograms are shown in Figure 2. The left image is a cross section of a human heart that shows all the four chambers, and the right image shows a cross section of the left ventricle.

In recent years, echocardiography has evolved into an important clinical method for identification and functional assessment of the entire spectrum of cardiac diseases because of its lack of radiation hazards; portability of instruments; and ability to carry real time visualization of internal organs [16, 17]. To diagnose the cardiac functional anomalies, cardiologists study regional wall motion, wall thickness, ventricular volume, ejection fraction etc. In the early years of technological development, cardiologists used to visually obtain a qualitative measure of these parameters, but visual processing tends to be tedious and subjective, and it has poor reproducibility [18, 19]. Recently, computer assisted processing has received increased attention, because in addition to efficiency and reproducibility, it

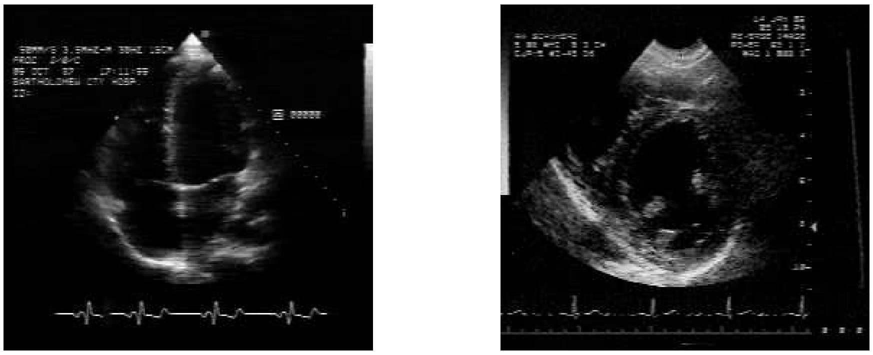

Figure 2: Two dimensional echocardiograms: a long axis view(left), and a short axis view.

provides reliable quantitative results [14].

Although some alternative techniques such as optical flow by Mailloux *et al.* [20], image flow by Chu *et al.* [21], and blob tracing by Hestenes *et al.* [22], have been proposed for direct estimation of heart wall motion and segmental shortening, *extraction of wall boundaries* is considered as an important step towards obtaining a large group of cardiac parameters such as regional and global motion, ejection fraction, ventricular volume, etc. Secondly, the extracted borders can be used for qualitative study through direct visualization.

Generating an initial estimate:
Extraction of the heart wall from 2DE can be viewed either as an edge detection problem, where heart wall contours are to be extracted [23], or as a thresholding problem, where the wall region is to be separated from the background [24, 25].

Edge detection is a popular contour extraction method in optical images processing [26, 27]. To detect the object contours, a typical edge detection algorithm goes through the following two steps. 1) Enhancing the image regions with high gray level gradients. 2) Extracting the contours either by detecting locally characterizable (usually maxima or zero crossing) points, or by thresholding and thinning. These techniques are effective on optical images, but on echocardiograms these techniques yield unsatisfactory results. The bottom row of Figure 3 shows the edge images generated using the Sobel's edge operator to an optical image of a hand drawn sketch (top-left) and to a 2DE image (top-right). The extracted edges of the optical image are satisfactory, but the edge image of the 2DE has many false positives and false negatives owing to high noise and texture. Cardiologists are interested in extracting the structural edges that correspond to heart wall boundaries, but the conventional edge detectors being simple gray level gradient detectors, can not distinguish the textural edges from the structural edges.

The problems of fragmented contours and false positives and negatives can be reduced if thresholding is used to detect the heart wall. A variety of thresholding techniques have been developed to process optical images [28, 29, 30, 31]. Since thresholding generates regions rather than the boundaries, the contours obtained by tracing the borders of the thresholded regions are less fragmented than the contours detected using edge operators.

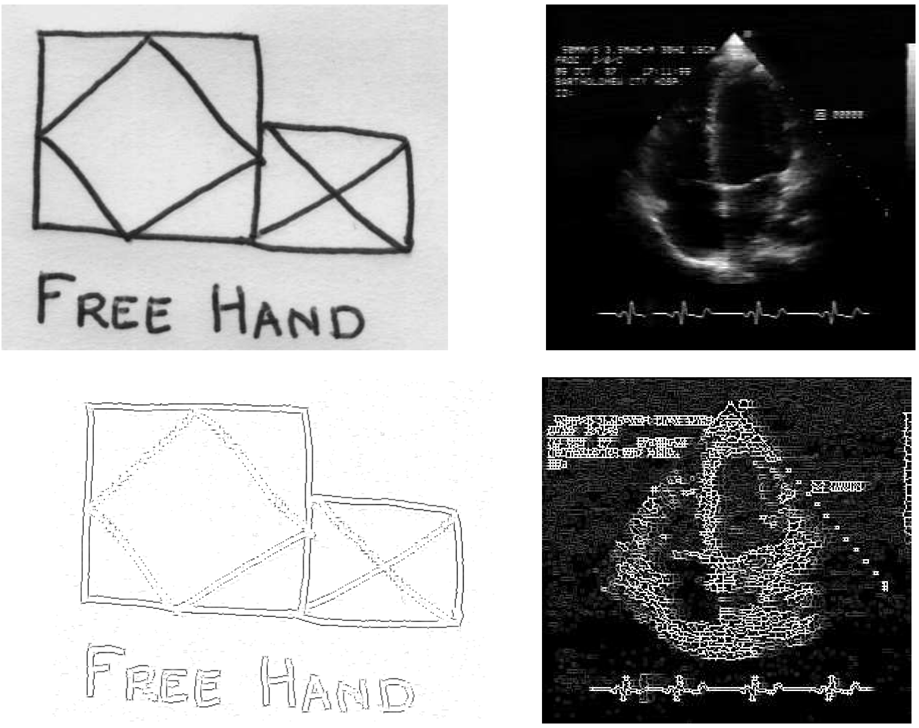

Figure 3: Edge image obtained by thresholding the Sobel enhanced images of an optical image of freehand drawing (left) and a two dimensional echocardiogram.

On the other hand thresholding, being level sensitive, may lose some weakly illuminated contours. In Figure 4 We show two thresholded images generated using Otsu's thresholding algorithm [32]. The left image corresponds to an optical image where the thresholding satisfactorily separates the object from the background. The right image corresponds to a 2DE, and it does not provide a good estimate of the heart wall region.

These processing difficulties of echo-images can be attributed to inherent limitations of ultrasonic imaging and complexity of the imaged environment.

I. Inherent system limitations:

The sound beam generated by the ultrasound scanners have side-lobes which introduce spurious structures in the echocardiograms. To get uniform focus throughout the scan-length the sound beam is defocused. This improves axial resolution at the cost of lateral resolution, and introduces blurring and aliasing of the tissue structures. In addition, the sound wavelengths usable for echocardiography exhibit orientation dependent drop-offs because of specular reflections. Finally, the automatic time gain compensation provided for the weak signals that have traveled larger distances is only an approximate compensation [33].

II. Complexity of the scanned environment:

Echocardiograms portray a complex structure of human tissues in and around the heart, and hence there is considerable aliasing between the cardiac wall echoes

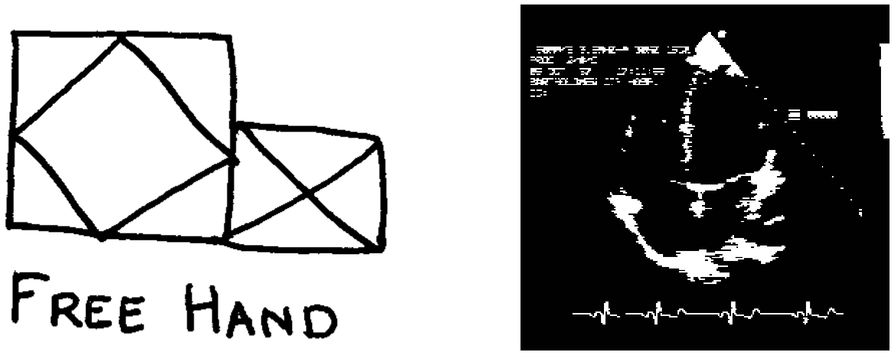

Figure 4: Thresholded output of a freehand drawing optical image(left) and a two dimensional echocardiogram.

and the echoes from the surrounding tissues. Even within the similar data-area the echodensity (gray value) is not uniform.

As explained, poor quality of the data combined with the complexity of the scanning environment, make the automatic heart wall extraction unreliable. Special thresholding and edge detection algorithms have been developed for processing 2DE images [34], but owing to the unreliability of the results, none have been commercialized. We feel that the reliability can be improved if the domain dependent knowledge is used in the heart wall extraction process. we provide the required knowledge through collaborative processing, which facilitates an active interaction between an expert and the machine.

Collaborative refining of the estimated heart wall:

By collaborative refining we mean, that an expert operator supervising the computer generated estimates indicates the misclassified regions either by pointing or by circling, and the computer algorithms compute the precise extents of the indicated regions, and perform the intended correction.

This problem involves two separate issues.

- Firstly, providing the essential mechanism so that the supervisor can: 1) interact in a natural way, 2) refine the estimates iteratively, and 3) recover from the erroneous corrections.

- Secondly, the computer algorithms to compute the precise boundaries of the regions indicated interactively either by pointing or by circling.

A satisfactory solution to this problem should address both the image processing requirements to compute the intended boundaries, and the psychophysical factors involved in visual suggestions so that the operator is not surprised or annoyed by the corrections.

2.1 Brief review of the published work

Increasing use of two-dimensional echocardiograms (2DE) for diagnosis [35, 16], has encouraged increased efforts to computerize the quantification of cardiac parameters. Visual processing of echocardiograms is time and labor intensive, and usually provides qualitative and subjective results [36]. In contrast, computer assisted techniques are efficient and provide quantitative reproducible results [37, 38].

Conventionally, heart wall boundaries were manually traced using a variety of tracing instruments such as light-pen [39, 18, 40], sonic digitizer [41], grease pencil [42], trace paper [43], acetate overlays [44], etc. Manual tracing is tedious and inefficient, and the contours have low reproducibility [18, 45].

A variety of methods for automatic and semiautomatic extraction of cardiac wall have been reported. These methods can be classified into 1) *thresholding* [25, 46, 47, 48, 24], 2) *edge detection* [49, 23, 50, 51, 52], and 3) *model* [53, 54, 55, 56, 57, 58, 59, 60, 61] based techniques.

2.1.1 Thresholding based techniques

Thresholding based techniques work on the principles of classical optical image thresholding schemes, but are modified to account for the 2DE data characteristics. Revankar and Sher [25] used the regional morphological enclosures to modify the default global threshold according to the spatiotemporal coherency, so that the noise was suppressed and the contours were preserved. Siler *et al.* [46] proposed threshold selection by regional histogram analysis and made it adaptive by Geiser's method [62]. Zhang *et al.* [47] used local temporal coherence to select a threshold. They picked the threshold that maximized the number of boundary pixels between neighboring 2DE frames.

Usually thresholding schemes do not discriminate between the registered echodensities of uninteresting cardiac artifacts, and that of heart wall. Hence the thresholded structures tend be an image of the heart wall overlapped by uninteresting structures. In addition, the data dropout regions are usually wrongly classified. To overcome this difficulty many researchers have proposed the use of interactive specification of the regions to be classified [24, 48].

2.1.2 Edge detection based techniques

The Laplatian and Spatial difference operators [49], Sobel's edge operators [23], etc. have been used to extract heart wall contours. These methods yielded disconnected and jagged edges which were smoothed either by initial spatial smoothing of the echocardiograms or by direct smoothing of the detected edges [50].To obtain consistent continuous contours a large number of researchers have used interactive methods to decide the center of a heart cavity, and detected the edge points by radial echodensity gradient analysis [51]. They corrected the missing edge points and the erroneous edge points by interpolation. Feng *et al.* [52] generated the edge points using fuzzy reasoning on the edge points detected by a Gauss-Laplatian edge operator, and the global intensity gradient map acquired from human experts. Later, they splined the boundary points to obtain a smooth endocardial border.

We studied the Sobel's and a new orientation independent edge detector [34, 63], and results were not encouraging on our data set.

2.1.3 Model based techniques

Deformable models [57, 58] and regional probability models [59, 61] have been used to extract inner wall contours. Staib *et al.* [57] placed an approximate contour model on the location of interest and deformed it according to a set of flexible probabilistic constraints to match with the corresponding heart wall. The constraints were obtained by elliptic Fourier decomposition of a set of manually traced boundaries. Duncan *et al.* [58] modeled the inner wall boundary as a thin flexible rod whose undeformed state was derived from the manual measurements made on a group of normal patients. The amount of effort required to deform any part of the contour from its normal state to its final shape was given by the local curvature difference between the contour and the mean normal contour at that location. They defined a weighted sum of this difference as the bending energy, and claimed that it uniquely characterizes various heart deformations.

Van Bree *et al.* [59] generated a probability surface of the expected border locations using a large clinical data-base, and used the surface model to overlay a series of contours on the test images. They selected a set of optimal contour points using the overlaid contours and detected edge points, and splined to get smooth contours. Friedland *et al.* [64] defined one dimensional Markov random fields with radii emanating from the center of gravity as the variable, and detected the optimal contour by minimizing an empirically determined energy function through simulated annealing. The energy function was a linear composition of the elements that represent detected edges, wall smoothness, temporal continuity, and volume maximization.

The above methods use a standardized initial template of the boundaries, thereby reducing their sensitivity to wall deformations and image specific expert opinions. We use the ideas proposed in the deformable modeling techniques [57, 58, 4] for interactive refinement.

2.2 Our approach to extract the heart wall

Figure 5 shows an overview of our collaborative processing scheme. We have developed a graphic package in the X-environment that allows an operator to view both the original and the processed images side by side. It facilitates animation, forward and reverse scan, picking points or inputting contours, masking regions, binary expansion and contraction, changing the color maps and display constants, etc.

Initially, a morphologically influenced, linear time, thresholding scheme generates an estimate of the heart wall in all the time frames. The estimate is displayed along with the corresponding 2DE. The operator uses the visualization facility to supervise the estimate. If any misclassified regions are found, he indicates them interactively either by pointing or by circling [67, 15]. In our scheme, the interactive inputs are considered as approximate suggestions, and not as accurate descriptions.

All the interactive suggestions undergo a data dependent refinement, before execution. Our region growing algorithm finds the exact contours of the pointed regions, and our new

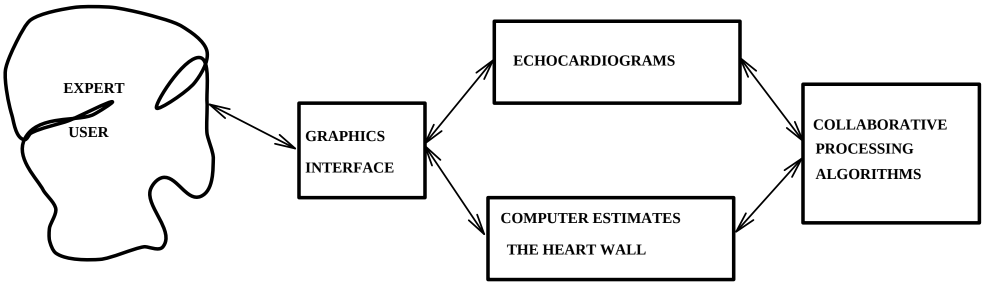

Figure 5: Overview of our collaborative scheme

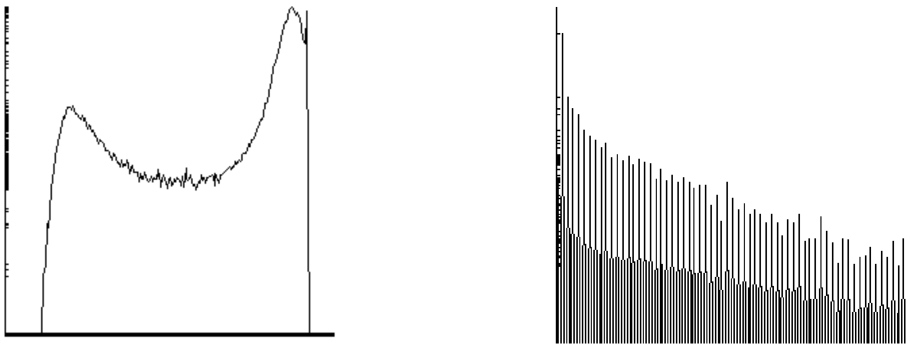

Figure 6: Histograms of the gray level distribution in an optical image of a freehand sketch (left) and a two dimensional echocardiogram.

deformable modeling algorithm captures the exact contours of the circled regions. Both of these algorithms account for the visual attention map of a human operator [6, 7, 8].

After the first stage of corrections, if the updated estimates of the heart wall were satisfactory, they can be used for direct quantitative measurements [44, 43, 40], including the measurement of motion [56, 81]. If the estimates were not satisfactory, they can be iteratively updated by circling or picking some more points on the misclassified regions.

2.2.1 Initial estimation of heart walls by thresholding

Echocardiograms portray a complex structure of human tissues in and around the heart, and the image grey level distribution is not statistically bimodal, *i.e.,* there is no distinctive contrast between the cardiac wall data and the surrounding blood volume data. This is apparent in Figure 6, where the left image is the histogram of an optical image of a hand drawn line sketch, and the right image is the histogram of a long axis 2DE. Hence, extraction of the cardiac structure or detection of wall boundaries using conventional thresholding results in noisy images with jagged edge patterns. The wall thickness variation is an important measure used for diagnosis, and it varies with the variation in the level of the threshold [25]. Therefore, the precision of the selected threshold value is more critical in processing 2DE, than it is for processing optical images of text or line diagrams, where the thickness information is often ignored [82, 83].

Ideally, a thresholding scheme must generate a smooth and continuous hear wall structure that correlates with the echo data. In other words it must satisfy the following criteria [84, 85]:

- eliminate noise speckles on the background or on the object
- preserve the boundaries and wall thickness
- generate a smooth heart wall boundaries
- fill-in the weakly reflecting parts of the heart wall.

To achieve these ideal requirements, the selected threshold must be high enough to suppress false positives on the background, must be low enough to fill-in the holes in the object region, must be boundary sensitive so that spreading, erosion, and jagging of boundaries do not occur, and at the weak reflection regions, it must be lower with edge preserving and noise suppressing properties. We develop a thresholding scheme that approaches these ideal requirements.

The 'state of the art' ultrasound systems allows us to make 30 to 60 scans per second [86]. Hence every time slice takes only a few milliseconds. The motion of the heart wall is relatively slow and it rarely moves more than about 2mm in $\frac{1}{30}$ of a second at its maximal velocity. Considering the pixel width of approximately 0.8mm, there will be temporal coherency that is comparable to spatial coherency of the data [47]. To exploit both spatial and temporal coherency of the data, we treat a sequence of 2DE as a 3D image, with two spatial coordinates (x, y) and time t as the third coordinate.

We define the morphologically adaptive threshold $T(.)$ at a point as follows:

$$T(x, y, t) = g_t + k(g_t - N(x, y, t)) \tag{1}$$

where g_t is the computed global threshold of the 2DE at time slice t, k is a smoothing constant, and $N(.)$ is the average gray value of the best fit regional morphological template. The best-fit morphological template is determined by finding the three dimensional (3X3X3) enclosure that has the average gray value that deviates the most from the global threshold g_t. A two-dimensional representation of these enclosures is shown in Figure 7. Our threshold selection technique [25] approaches an ideal threshold in several ways. It suppresses the formation of speckles on the background because $N(.)$ is small and the threshold is large, and it suppresses holes in the object because $N(.)$ is large and the threshold is small. Two examples of the outputs of this thresholding scheme are shown in Figures 8 and 10.

Further, to improve the reliability of this thresholding scheme, we have done following two improvements:

- The wall thickness is controlled by the default global threshold g_t. We have improved the default threshold selection by facilitating interactive pointing of the septum (wall

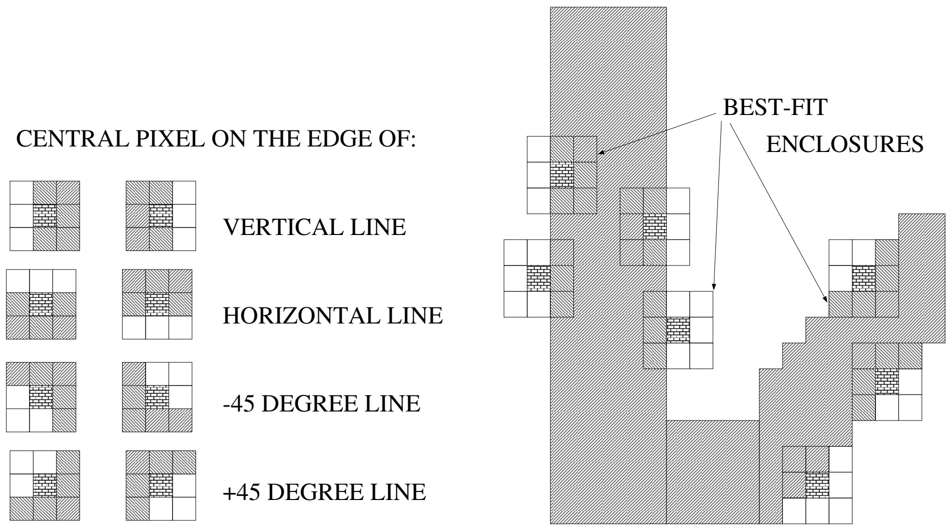

Figure 7: 2D morphological templates, and their best-fit positions are shown with reference to a binary image.

between right and left ventricles) on end-diastole or end-systole time frames, which has a known thickness. We select a threshold such that the thickness of the thresholded pattern approximates the known thickness.

- If the default global threshold is assumed to be constant throughout the image, it may result in losing the weakly reflecting areas. We improve this by using adaptively varying the threshold according to the regional grey level gradients between wall region and the background.

2.2.2 Refining the estimate by Collaborative updating

The thresholded outputs displayed in Figures 8 and 10 show that the thresholded images are only a crude estimate of the heart wall. The regions corresponding to the papillary muscles, bicuspid and tricuspid valves show high reflectivity to sound waves; hence the regions are either brighter or comparable to the heart wall region, and these regions also get classified as the heart wall in addition to the other spurious artifacts. At this stage simple data dependent schemes are unlikely to improve the estimates.

In our collaborative scheme, the expert indicates the misclassified regions either by picking points or by circling them. The precise boundaries of the regions indicated by the points are computed using a new *region growing* technique described below. Preliminary results of this scheme are encouraging [63].

We intend to use deformable modeling to get the precise boundaries of the circled region, because it is natural for such an application. Similar applications have been reported in the literature [5, 3, 4]. Once the boundaries of the regions are obtained, the regions are classified according to operator's suggestions, thereby generating a refined estimate of the heart wall.

Refinement by region growing:

Region growing is a popular method of segmentation [87]. Most region growing techniques techniques are developed for unsupervised segmentation of the images [88, 89], but we intend to develop a supervised segmentation algorithm, wherein an expert supervisor indicates the corrections by pointing at the misclassified regions. To facilitate natural supervision we account for both the human imprecision pointing and the extent of visual attention.

The goal of our point dependent region growing algorithm (supervised segmentation algorithm) is to extract the precise boundaries of the region indicated by a picked point, say x_0. To achieve this, We develop a measure $P(.)$ (path function) such that a region is grown around x_0 by collecting the points x_i such that $P(x_0, x_i) < C$, where C is an empirically determined constant.

To obtain $P(.)$, we model an intended region under the following assumptions:

1. Since each region $L(x_i)$ in the image is contiguous, and the study shows that visual sensitivities fall steeply with the distance from the point of attention [8], physical distance (P_d) defined by $P_d(x_0, x_1) = k_1.|x_0 - x_1|$, between any two points in an intended region must be small.

2. A change in the echodensity normally indicates a change in the tissue type, therefore echodensity transitions (P_t) between any two points in an intended region must be small. We call this measure the transition distance, and it is recursively defined as follows:
   $P_t(x_0, x_i) = 0$ if $||x_0 - x_i|| < \; spot - light$
   $P_t(x_0, x_1) = k_2. \min\{(P_t(x_0, x) + |g(x) - g(x_1)|) \mid x \in \{neighborhood \; of \; x_1\}\}$.
   where $spot - light$ is the spatial extent of uniform visual attention region around the picked point x_0.

3. Since the echodensity level characterizes the regions, there must be a density gradient between two neighboring regions. Therefore echodensity gradients (P_e) between any two points in an intended region must be small. We call this measure the *edge transgression distance* and it is defined recursively as follows:
   $P_e(x_0, x_0) = 0$ if $||x_0 - x_i|| < \; spot - light$
   $p_e(x_0, x_1) = k_3. \min\{(P_e(x) + |g(x) - g(x_1) - g_{avg}(x) + g_{avg}(x_1)|) \; |x \in \{neighborhood \; of \; x_1\}\}$.

   where $g_{avg}(.)$ is the average local echodensity.

and k_1, k_2, k_3 are experimentally determined normalizing constants.

Now we define the region indicated by the picked point x_0 as the region that lies within a predefined distance from x_0 with respect to the above distance measures, i.e. If the expert operator picks the point x_0, We gather every point x that satisfies the relation $P(x_0, x) < C$, where $P(x_0, x) = ||P_d(x_0, x), P_t(x_0, x), P_e(x_0, x)||$. In other words, we describe the intended region $L(x_0)$ as:

$$L(x_0) = \{x | P(x_0, x) < C \; \wedge x \in Image\} \tag{2}$$

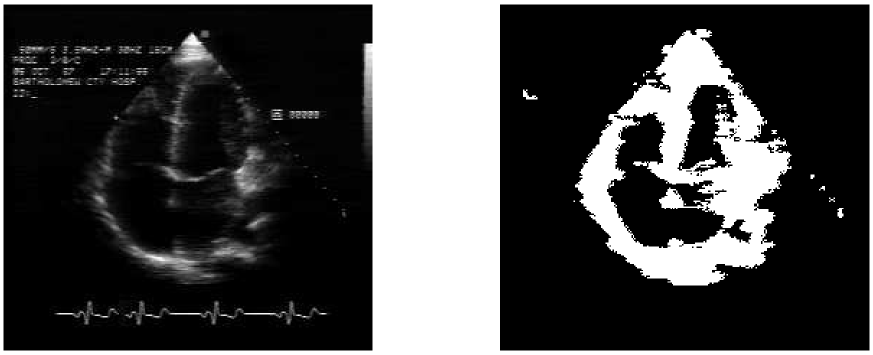

Figure 8: The original 2-dimensional echocardiogram (left) and the thresholded output.

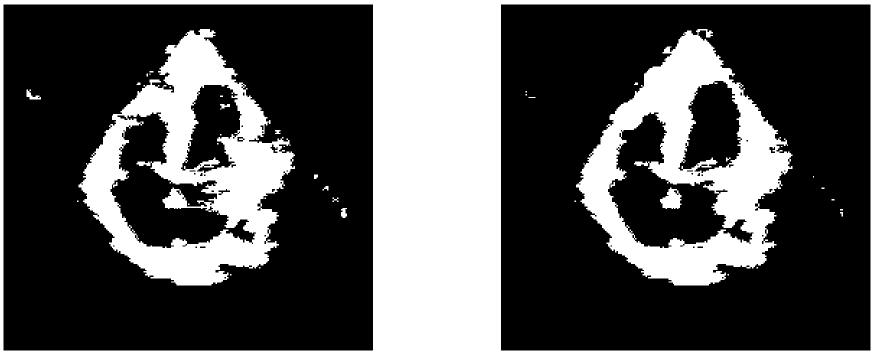

Figure 9: Interactively refined outputs: Refinement after picking a point in the top-right chamber (left), and refinement obtained by picking few more points.

All distance measures are computed on the original image. Once the intended regions are computed, they are added to or deleted from the earlier output to get a refined output.

Preliminary results of refinement of this model have been encouraging [63]. Some examples of updating by picking points are shown in Figures 8, 9, and 10.

Refinement by deformable modeling:
In general deformable modeling algorithms seek global minima of a heuristically defined energy function through some regularization method. The existing methods use a standard starting contour with a designated initial energy, and deform it iteratively to lower energy states, and stop the computations when the change in energy from one state to the other is below an empirically determined constant. These techniques are known to be unstable, and the termination and accuracy of the results depends on the good starting point.

We intend to differ from these schemes in the following two significant ways.

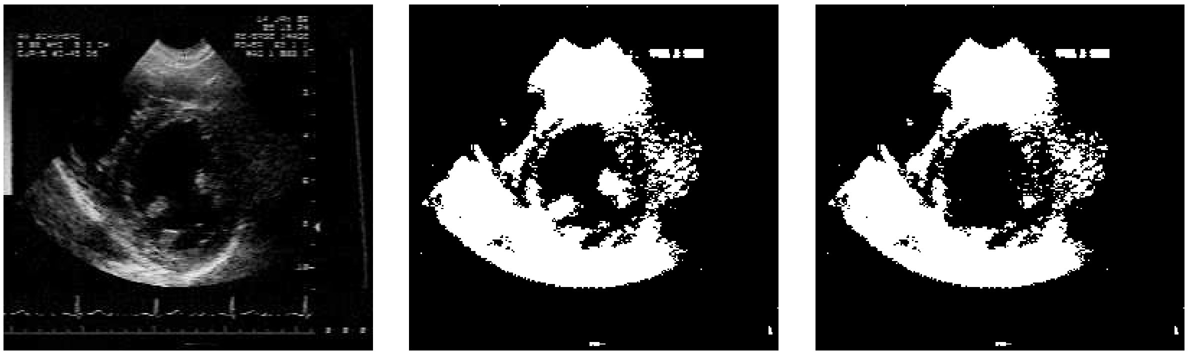

Figure 10: A short axis 2DE (left), thresholded output(left), and the interactively refined output.

- Firstly, in our scheme the initial contour is interactively specified by the user, hence unlike the standard techniques, We have to develop a new method to calculate the initial energies of the input contours.
- Secondly, we must find a solution that satisfies the operators visual attention model, otherwise the results of global minimization may surprise the operator thereby making the interaction unnatural and non-collaborative.

Sometimes 2DE data has large dropouts. Currently such regions are filled either by linear interpolation [90] or by splining [24, 91]. We intend to study the feasibility of solving this problem using *deformable open contours*. The same scheme could also be used for collaborative correction of sections of misclassified boundaries or for correction of thickness of a section of the wall.

We have implemented an initial tool for inputting a contour and deleting the enclosed region.

3 Technical relevance and contribution of the research

Extracting objects with nonrigid motion as opposed to rigid objects is a complex underdeveloped area of computer vision. For this reason, previous applications of this technology for extraction of the heart wall have produced limited results, and are unsatisfactory for general clinical use.

This is the first attempt to incorporate a psychophysical model of human visual attention map for interactive processing of digital images. We call such an interaction "collaboration," to distinguish it from the classical interactions where a master-slave communication is facilitated.

This research should produce significant benefit to supervised image segmentation, natural human interaction with computers and digital imaging as applied to the recognition of flexible images in general, and to echocardiographic images in particular. Using already developed state of the art algorithms together with newer algorithms that we develop, it will be possible to improve the ability of the computer to track moving heart wall. Furthermore, by developing collaborative tools that complement computer and human operator abilities, we expect to markedly enhance the heart wall tracking ability of the machine, and facilitate the development of a practical, convenient system that could handle bulk amounts of average quality echocardiographic data in a general clinical setting.

The envisaged system allows an expert to supervise and improve the estimate generated by the segmentation algorithms. This improves reliability and eliminates human intervention when processing good quality images. The ability to interact naturally, 1) may help the expert spend less time in learning the technology, and 2) may result in higher acceptance in the established medical community.

4 Conclusions

We have described a supervised image segmentation method that facilitates reliable separation of heart wall from two dimensional echocardiograms. In the interaction between an expert and the segmentation algorithms, the human expertise is complemented by the precision, efficiency, and reproducibility of the algorithms. To facilitate a natural interaction, we account for human imprecision and the attention distribution map, thereby simulating a collaborative environment.

Since this is the first published attempt to utilize human visual attention map for computer interaction in general, and for segmentation and deformable modeling algorithms in particular, a successful implementation will be a significant contribution to the field of human-computer interaction and computer vision.

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