4. Performance Evaluation and Results

Quality plays a very important role. The good quality of image will give a good diagnosis. Quality of image itself depends upon the cost and time required for evaluation of an image. Quality can be refer to:

a. a specific characteristic of an object

b. the achievement of excellence of an object

c. the essence of an object (the quality)

d. the meaning of excellence itself

The first meaning is technical, the second practical, the third artistic and the fourth metaphysical. All four have good meanings, and therefore the meaning of quality, are synonymous with good. There are two kinds of quality measures:

- Objective Evaluation of Image Quality
- Subjective Evaluation of Image Quality

4.1 Objective Evaluation of Image Quality

There are many methods provided for the measurement of image quality. Various algorithms have been developed since last three decades. This step involves the object recognition. As in medical imaging, all diagnosis are based on the symptoms of a patient and these symptoms can be proved by comparing with objective evaluation factors. As human viewer separates object of interest from an image, then correlate it with objective quality measures through feature extraction technique.[1] The objective evaluation techniques are mathematical models that successfully emulate the subjective quality assessment results, based on criteria and metrics that can be measured objectively. The objective methods are classified, according to the availability of the original video signal, which is considered to be in high quality.

The most traditional ways of evaluating the quality of digital image processing system is counting of the Signal Noise (SNR) and Peak Signal Noise (PSNR). PSNR is one of objective quality metrics - metrics that can be automatically computed by a computer program. The PSNR is most commonly used as a measure of quality of reconstruction in image compression etc. It is most easily defined via the mean...
squared error (MSE) which for two \( m \times n \) monochrome images \( I \) and \( K \) where one of the images is considered a noisy approximation of the other is defined as:

\[
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \| (i, j) - k(i, j) \|^2
\]  \hspace{1cm} --- 4.1

The PSNR is defined as:

\[
PSNR = 10 \log_{10} \left( \frac{MAX^2_i}{MSE} \right) = 20 \log_{10} \left( \frac{MAX^2_i}{\sqrt{MSE}} \right)
\]  \hspace{1cm} --- 4.2

**Signal to Noise ratio**

The signal-to-noise ratio, \( SNR \), can have several definitions. The noise is characterized by its standard deviation, \( s_n \). The characterization of the signal can differ. If the signal is known to lie between two boundaries, \( a_{\text{min}} \leq a \leq a_{\text{max}} \), then the \( SNR \) is defined as:

\[
SNR = 20 \log_{10} \left( \frac{a_{\text{max}} - a_{\text{min}}}{s_n} \right) dB
\]  \hspace{1cm} --- 4.3

Bounded signal -

If the signal is not bounded but has a statistical distribution then two other definitions are known:

\[
SNR = 20 \log_{10} \left( \frac{m_a}{s_n} \right) dB
\]

Stochastic signal - \( S \) & \( N \) inter-dependent

\[
SNR = 20 \log_{10} \left( \frac{s_a}{s_n} \right) dB
\]

\( S \) & \( N \) independent

Where \( m_a \) and \( s_a \) are defined above.
4.2 Subjective Evaluation of Image Quality

Here, in subjective analysis, by applying different techniques on images the region of interest gets separated and features are extracted from the image. The main goal of many objective video quality metrics is to automatically estimate general user's opinion on a video processed by the system. But the best way to find out a user's opinion is just to ask them! Sometimes however, subjective video quality can also be challenging, because it may require a trained expert to judge it. Many subjective measurements are described. Their main idea is the same as in Mean Opinion Score [2] for sequences that are shown to the group of viewers and then their opinion is averaged to evaluate the quality of each video sequence, but details of testing may vary greatly.

The MOS is the arithmetic mean of all the individual scores, and can range from 1 (worst) to 5 (best).

Table 4.1: MOS Score

<table>
<thead>
<tr>
<th>MOS</th>
<th>Quality</th>
<th>Impairment</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>Excellent</td>
<td>Imperceptible</td>
</tr>
<tr>
<td>4</td>
<td>Good</td>
<td>Perceptible but not annoying</td>
</tr>
<tr>
<td>3</td>
<td>Fair</td>
<td>Slightly annoying</td>
</tr>
<tr>
<td>2</td>
<td>Poor</td>
<td>Annoying</td>
</tr>
<tr>
<td>1</td>
<td>Bad</td>
<td>Very annoying</td>
</tr>
</tbody>
</table>
Following experiments are shown below in which the quality of image gets improved and the techniques which are applied on these images is as per the region of interest (ROI).

**Case Study 1: Detection of Breast Cancer (ROI) using Ultrasound Imaging**

Breast Cancer is one of the most common and serious public health problems. For diagnosis of the disease and to improve quality of life, Ultrasound imaging remains as an important image modality among the varieties of cancer detection techniques.

The underlying premise for breast cancer screening is that it allows for the detection of breast cancers before they become palpable. Breast cancer is a progressive disease, and small tumors are more likely to be detected in early stage of disease, have a better prognosis, and are more successfully treated [3]. Mammography is the Gold Standard for imaging of the breast and detection of early breast cancer. However, this sensitive screening and diagnosis technique has high false-positive (FP) rate. Some of the limitations are: inability to change image contrast or brightness, problem in detection of subtle soft tissue lesions (dense glandular tissues), and difficult to archive. Ultrasound uses some harmless and painless sound waves to produce a visual picture of the breast. Ultrasound is non-invasive, portable, and versatile, it does not use ionizing radiations, and it is relatively low-cost. Ultrasound image analysis in general is complex due to data composition, which is described in terms of speckle information. Upon visual inspection, speckle consists of a relatively high grey level intensity, qualitatively ranging between hyper-echoic (bright) and hypo-echoic (dark) domain [4]. In the analysis of medical images, the advices from medical doctors are required to inspect the suspected regions, for benign lesions and/or malignant legions. The algorithm for this is described with following figure:

![Figure 4.1: Region of Interest (ROI) Detection](image-url)
Preprocessing

The performance of a high quality breast ultrasound examination not only depends on the scanner, but also requires a trained and experienced examiner with knowledge of the normal echo anatomy of the breast and the changes caused by the pathology. To guarantee the homogeneity in ultrasound images, histogram equalization is applied to the images.

Filtering

A good filter is very important in Ultrasound imaging. The fundamental requirements of the noise filtering methods for medical images are:

1. It should not lose the important information of the object boundaries and detailed structures
2. It should efficiently remove the noise in the homogeneous regions, and, it should enhance morphological definition by sharpening discontinuities [5].

The quality of ultrasound images is poor, which is affected by multiplicative speckle noise and artifacts that causes information loss. Different types of filtering methods are available, such as: Anisotropic diffusion, nonlinear diffusion filtering, Gaussian filter, Average filter, and Laplacian filter. Diffusions correspond due to additive noise. In cases where images contain speckle, anisotropic diffusion will actually enhance the speckle, instead of eliminating the corruption. As nonlinear diffusion have its ability to reduce noise while preserving (or even enhancing) important features of the image, such as edges or discontinuities; which is more better than the linear diffusion (alias Gaussian filtering or linear scale-space representation) which not only removes noise but also blurs and dislocates edges. Hence, the nonlinear diffusion filtering method is used to produce edge-sensitive speckle reduction.

Segmentation

Segmentation is a process to divide an image into its constituent parts. Segmentation of certain medical images into regions of different tissues enables automatic measurements. The watershed transform is a well established tool for the segmentation of images. Instead of using the image directly, the transform uses a gradient image extracted from the original image [6]. In geography, watershed is the ridge that divides areas drained by different river systems. A catchments basin is the geographical area draining into a river or reservoir. The watershed transform applies
these ideas to gray-scale image processing in a way that can be used to solve a variety of image segmentation problems. Direct application of the watershed transform to a gradient image usually leads to over-segmentation due to noise and other local irregularities of the gradient [7]. Speckle noise and artifacts can be removed by implementing Gaussian blurring of ultrasound images. Gaussian blurring can smooth the images and at the same time filter out the edges information. An approach used to control over-segmentation is based on the concept of marker, namely, Marker-Controlled Watershed Segmentation.

Detection of lesion candidates

The location of the Region of Interest (ROI) is crucial to find the location of the abnormal lesions. The location of the abnormal lesions requires the specification of both position and orientation.

In this case, two methods have been applied to the images to specify the point of interest, namely, statistical analysis and fractal analysis. The suspected lesions, benign and malignant, have lower intensity compared to the normal tissue/anatomy. This criterion is used in statistical analysis. We calculate the local mean of each segment, centered at the center of gravity (cog), with radius 9. With radius 9 the clarity of the images is better when it is compared with 3, 5, 7, etc. Hence radius 9 is used in this study. The minimum point of the local mean is the point of interest.

Fractal analysis has been studied in many applications, such as, medical image analysis, satellite image analysis, and textures analysis in an image. A modified fractal dimension calculation based on dimension normalization technique [8] is carried out to extract the information of each segment in ultrasound breast images. In modified fractal dimension, N is the first normalized by the surface area covered by window size, L. The normalized can then be related to maximum gray level H by

\[ N_n = N / (L \times L) = H_f \]  \hspace{1cm} --- 4.4

In the case of segments, since all the segments with uneven areas, the surface area, L ×L, is substituted by the total area of the segment [9].

\[ f = \log \left( \frac{N_n}{H} \right) \]  \hspace{1cm} --- 4.5

Where ‘f ’ is partial fractal surface dimension. The modified fractal surface dimension, can be obtained by adding physical dimension to
\[ D_m = 2.0 + f \]

In fractal analysis, the legions have rougher surface compared to the normal regions. And also have lower intensity than normal tissue or region. This criterion is used in statistical analysis. We calculate the local mean of each segment, centered at the center of gravity (cog), with radius 9. The minimum point of the local mean is the point of interest. In detecting the point of interest, the minimum is selected.

**Combination of lesions**

In order to obtain the region of interest, the criterion of the neighborhood segments is investigated. The segment is combined with the segment of interest if it has low intensity and low value of \(D_m\). The experimental procedure is:

1. Original Image
2. Histogram Equalization
3. Filtered Image
4. Watershed Segmentation
5. Mapping of Watershed Function
6. Labeling of Watershed Function
The graphical representation for this method is

Figure 4.3: Graphical representation

Figure 4.3 (a) shows the minimum local mean shown at the segment number 50 is the point of interest. And 4.3(b) the minimum shown the segment number 50 is the point of interest. From Figure (f), the statistical analysis (local mean) and fractal analysis $D_m$ are calculated for each segment. The graph in figure 4.3 shows the minimum point of the local mean and $D_m$.

According to radiologist the comparative results for 10 patients are obtained through this are.
### Table 4.2: Analysis of ROI Detection using above methods

<table>
<thead>
<tr>
<th>Method</th>
<th>Positive</th>
<th>Negative</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local mean</td>
<td>07</td>
<td>03</td>
<td>70%</td>
</tr>
<tr>
<td>Fractal Analysis</td>
<td>05</td>
<td>05</td>
<td>50%</td>
</tr>
</tbody>
</table>

Fractal analysis is not accurate in detecting ROI. The reason is that the value of $D_m$ is highly dependent on the characteristics of the neighborhood pixels. The lesions with high intensity and homogenous may produce very low value of $D_m$. However, referring to the graphs in figure 4.3, there is a clear cut of the low value point for fractal analysis compared to statistical analysis.

The statistical analysis is accurate in cysts and malignant detection, but not in the case of fibro-adenoma. Most of the positive cases in the experiment are cysts and malignancies, the lesions with low intensity. In the other hand, the negative cases in this experiment are fibro-adenomas.

### Case Study 2: Detection of follicles in ovary using ultrasound

Ultrasonic imaging has become an indispensable tool in many medical examinations. A direct diagnostic value of such a method relies upon a skilled and objective interpreter of the acquired images. Therefore, assistance of computer-based processing algorithm may play an important role on the way to a successful recognition of crucial information contained in the ultrasound recordings.

Digital images are composed of big set of small rectangular elements - pixels. The digital images are treated as grids or matrixes. [10, 11] Pixels hold mostly grey level intensities (possible are also other values, e.g. textures, colors, motion gradients). The object recognition in the digital image processing sense means grouping (processing, transforming) the grey levels in such a manner that resulting groups (regions) of pixels representing an object in the image.

#### 2.1 What are Follicles?

Follicles are:
- Fluid filled sacs.
- Appearing as oval regions in ultra sonographic images
A complete understanding of follicle, i.e. a sac containing ova, dynamics inside the ovary is crucial for the field of genetic engineering. Monitoring follicles over entire cycle is especially important in human reproduction. The outcome of a pregnancy is dependent upon the quality of the embryo. This, in turn, is dependent in part upon the quality of the female gamete oocyte contained in the dominant follicle (dominant follicles are those that grow and have potential to ovulate at the end of the follicular phase) and, therefore, the quality of the follicle itself which supports oocyte growth and maturation. Not all dominant follicles ovulate and of those that do, not all are of sufficiently high quality to result in pregnancy.

Here the main task is successfully characterize dominant follicles from the set of follicles inside the ovary. To characterize successful dominant follicles, the follicles must be compared with unsuccessful dominant and subdominant follicles and their interactions examined. For a comparison to be possible individual large and small follicles must be identified and their development monitored over a number of days. Follicles can be monitored on many different manners; the best way of monitoring is with non-invasive methods, e.g. ultrasonography with frames of the ovary, grabbed on either way, and with appropriate criteria (right shape, antral edge quality, size and echogenicity) the follicles (and also its type) can be identified and required analysis accomplished. Today, the monitoring of follicles with the help of computer automatically and human interaction A doctor examining 30 women a day during their entire cycle (ultrascan woman, freeze the ultrasound image in the best position of the ovary, measure every follicle inside ovary by hand, store the results, repeat this procedure for both ovaries - left and right). This work can be very time consuming and with human error. That was the main reason behind developing this methodology to study this with more accuracy and less duration for automatic location and analysis of follicles in the ovary. In the image processing sense, we are dealing with an ultrasound image sequence of the ovary. Our work is still in the initial stage, so we are able only to present intermediate results. A core of the application is an algorithm analysing the follicle dynamics. Currently, we are analysing only few images and its sequence at a time.
2.2 Problems with Ultrasound Machine Detection of Follicles

Most common problems with ultrasound machine in detection of follicles in ovary are:

- It is time consuming.
- Expert doctor is required for detection of follicles.
- If water retention is not good, it is difficult to detect.
- Manual measuring and storing for further comparison is also difficult.

To overcome the above problems we use different techniques to improve the quality of image further help for diagnosis. While capturing an ultrasound image factors like contrast, blur, distortion and noise are considered and the good quality image gets acquired. The original image is taken from Telemed’s PC based Ultrasound machine with 3.5 MHZ electronics probe with their software is used in the entire machine for its operation. The image obtained is a gray scale $576 \times 768$ image. Its resolution is 96 dpi. Here, the image gets captured by the doctor and the endometrium wall is on the top. While at the center we can see the follicles but we cannot see the boundary of follicles, by moving the probe forward and backward directions we can get the boundary of follicle even by expert as the boundaries having a blurred. To avoid these complications computer algorithms are developed for the improvement of results.

The block diagram for this system is as follows:-

![Block Diagram](image)

Figure4.4: Block diagram recognition of follicles

The typical object recognition scheme has the following structure: the first step of this scheme is an image acquisition (e.g. with the CCD camera and frame grabber). The images obtained are usually of such a poor quality (in practice the conditions of image acquisition are everything but ideal) that the extraction of the
objects (using computer) only from unprocessed grey level intensity digital images is almost impossible (left image). Original images are because of this fact sequentially processed until object extraction is possible. Initially, there is an image preprocessing stage where the image noise found is suppressed with some filters or local operators (e.g. Gaussian, low-pass or median filter). Generally, image preprocessing enhances desirable image (object's) features. After preprocessing, the pixels which actually belong to the object have very similar values of certain features. The image segmentation follows, which can be done in many different ways, the most common methods are image segmentation based on thresholding where a few thresholds segment the entire image into regions (e.g. binary thresholding all the pixels having a specific feature smaller than threshold form the first region, all the remaining pixels are in the other region), edge based segmentation where the object's boundary is traced, and finally, region based segmentation where the regions are searched directly (e.g. region growing or splitting). In the middle image from following figure the segmentation result obtained after simple thresholding of the original image is shown.

Each obtained region is then described by some features or parameters. The last step of this scheme is classification where these regions are usually compared with perform (representative object) and after that accepted as the right object or rejected as a wrong one. The key point of a good classification is selection of appropriate features as well as a sufficiently large number of features. The right image from following figure depicts recognized ellipses after classification stage.

![Figure 4.5: Typical object recognition scheme.](image)

Original noisy image (left), two biggest regions are labeled after simple thresholding segmentation (middle), recognized ellipses (right).
4.3 Various Techniques for Ovarian Follicle Detection

There are various techniques used for follicle detection [4]

- Classical Image Processing Approach
- Histogram Equalization Method
- Prediction Based ovarian follicle detection
- Follicle Recognition & Cellular automata & neural networks
- Follicle Recognition using region growing algorithms
- Follicle Detection using watershed segmentation
- Hough transform

In most cases, firstly the problem is with capturing the ultrasound image. In this image acquisition process, exact probe and mode is selected and then image gets captured; but as in ultrasound images noise formation is more, and to suppress this noise various filters are used like Gaussian, low-pass, median filters, adaptive band-pass filters but as per expert still noise should be there. In ultrasound image speckle and additive noise (due to head of the probe) should be there. A new filter called as de speckle filters or Homogenous Region Growing Mean Filter (HRGMF) is used which is the combination of two median filters with different masks which preserves the edges. It means preprocessing stage is very much important for further analysis. In segmentation we can describe small and large follicles and follicles which are of dark (almost black) circular shapes. The task is to find all the dark regions in the image and then verify if these regions should be follicles. Dark regions are obtained with thresholding the image. Single threshold is determined with optimal threshold selection method. Thus, the binary subimage is generated. Then, all the black regions inside the ovary are labeled (identified) and processed. Finally, each processed region is described with parameters (area, perimeter, moments, eccentricity, compactness, bounding box, etc.). In last classification stage, every parametrically described region is evaluated. On the parameter basis, we decide about each region whether it is a follicle or not. At this point, additional knowledge about the problem is introduced into the algorithm (minimum and maximum size of the follicle, expected shape, etc.). Follicles are between 2 mm and 20 mm in size and they are of circular shape. This knowledge influences the predefined thresholds needed and criteria for the region classification. For classification we used three rules: area, compactness, and eccentricity. From the above we can recognize it as follicle of size of 8mm or 15mm.
etc. This can be calculated by measuring the diameter and comparing with the features it gets recognized. The area threshold is 220 (rule: area of follicle >220), compactness threshold is 40 (compactness > 40), and eccentricity threshold is 0.5 (eccentricity > 0.5). If a region satisfies all three criteria, then we say that this region is probably a follicle.

2. Discussion

Here the algorithm is developed for follicle detection in ovary using ultrasound image.
Table 4.3: Case-2 Flow-Chart:

- **Start**
  - Input Image
  - Convert from bmp to fit
  - Filter using IMFILTER
  - Filter Using HRGMF Filter
  - Edge Detection Using KIRSCCH Operation
  - Convert to BW using OPTIMAL thresholding & im2bw
  - Perform Edge thinning & Edge filling
  - Using IMHIST ( ), histeq ( ) estimate Ovary position
  - Perform Segmentation using optimal thresholding
  - **A**

- **A**
  - If Follicles = 2mm to 10 mm
  - Label the dark regions
  - Describe Regions with area, compactness
  - Recognise the image regions
  - Output image (DETECTED FOLLICLE)

- **Display message “Follicles not found”**
The steps included in this are

- Speckle noise reduction using HRGMF filter
- Edge detection using Kirsh’s operator
- Binarization of resulting image with optimal thresholding
- Morphological edge thinning
- Heuristic edge filling
- Histogram for ovary position
- Segmentation using optimal thresholding method
- Labeling dark regions
- Describing regions with area, eccentricity, compactness
- Recognize the region as follicle

Steps 1-6 are used for preprocessing, steps 7-8 for segmentation, step 8-10 for recognition of follicle.

**Preprocessing stage**

The original image captured by the ultrasound image contains additive noise due to head of the probe. In old days this noise was reduced by a median filter or a combination of median filter were used with different masks to reduce the noise, but in this case the edges are not preserved, so a new filter is used called as HRGMF (Homogenous Region Growing Mean Filter) or de Speckle filter. This filter detects the edges and blurs all image except those edges. This blurring removes noise while preserving edges. Koo and Park (1991) proposed a technique called the homogeneous region growing mean filter (HRGMF).

The idea of this HRGMF filter is: for a given pixel point, a local rectangular region centered at the point is defined (initial region). If this rectangular region satisfies a certain local criterion of homogeneity (this criterion can be obtained from the imaging system experimentally), it is taken as the seed region. Otherwise, the region is contracted subsequently until contracted region satisfies the homogeneity criterion. Once the seed region is determined in this way, the next step is to grow the homogeneous region by absorbing a thin, adjacent rectangular side region which has the same statistical properties as the seed region. This is repeated until there is no
more homogeneous neighbor on any side of the current region. Now, the mean of the pixel values of the grown homogeneous region is mapped onto the filtering point.

\[ R_i = I_i \sigma_{new}/\sigma \]

Where \( R_i \) is result image \( I_i \) is the \( i \)’th pixel of input image
\( \sigma \) is the mean value of input image \( \sigma \) new mean of result image

The image filtered with HRGMF filter is a basis for the whole subsequent analysis. From this image we try to estimate the ovary position. This task is accomplished as follows. First, the edge detector is used. We apply Kirsch’s filter for edge detection. The kirsch’s operator is

We experimented with a lot of other edge detecting operators (Sobel, Canny filter, LoG, etc.), but the Kirsh’s one gave the most satisfying results respecting the time consumption and efficiency.

Then the image is binarised (optimal threshold) and thinned. Because edges are very corrupted (ovary and follicles don't have very expressed edges), we correct them. A simple heuristic method is used for edge filling. Starting and ending point of the connected component (partial boundary) are joined (in the direction of straight line through both points) with edge pixel from the other connected component (edge pixel must be located in predefined zone near both pixels). From so processed image, the position of the ovary is estimated. The criterion used for estimation is that ovary is probably in a rectangle where the density of edges, i.e. white pixels, is the highest, since the ovary contains several regions belonging to the follicles. The density of edges is estimated by two histograms generated along x and y direction. The maximum value in both histograms is obtained. This maximum is a starting point from which two minima, one on each side of the maximum (for each histogram), are searched for. We define minimum as the lowest value before the histogram values start to increase significantly again (this minima are not necessary the global minima on both sides). With calculation of both minima along both directions, the rectangular area probably containing the ovary is defined (sub image with the ovary).
Segmentation Stage

In preprocessing phase, the rectangular area (sub image) containing the ovary was determined. Our task is to find all the dark regions in the sub image and then verify if these regions could be follicles. Dark regions are obtained with thresholding the sub image. Single threshold is determined with optimal threshold selection method. Thus, the binary sub image is generated. Then, all the black regions inside the ovary are labeled (identified) and processed. Finally, each processed region is described with parameters (area, perimeter, moments, eccentricity, compactness, bounding box, etc.).

Classification stage

In this stage, every parametrically described region is evaluated. On the parameter basis, we decide about each region whether it is a follicle or not. At this point, additional knowledge about the problem is introduced into the algorithm (minimum and maximum size of the follicle, expected shape, etc.). Follicles are between 2 mm and 10 mm in size and they are of circular shape. This knowledge influences the predefined thresholds needed and criteria for the region classification. For the classification we used three rules: area, compactness, and eccentricity.

The formulas are used for finding and calculating the following:

1. **Area:** Counting of region pixels will provide its area which can be

   \[
   Area = \frac{1}{2} \left[ \sum (i_k j_{k+1} - i_k + 1 j_k) \right] n^{-1}
   \]

   --- 4.7

2. **Eccentricity:** It is the ratio of the length of maximum chord and minimum chord. It is ratio of main region axes of inertia.

3. **Compactness:** It is the compact region in a Euclidian space is a circle.

   \[
   \text{Compactness} = (\text{region border - length})^2/\text{area}
   \]

   --- 4.8
Figure 4.6.1: HRGMF (De-speckle Filter)

Figure 4.6.2: Kirsh’s operator applied to initial region $7 \times 7$ de Speckle image followed by Optimal threshold 40) binarisation, thinning & heuristic edge filling

Figure 4.6.3: Sub-Image

Figure 4.6: Follicle Detection
### Table 4.4: Subjective Analysis:

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Follicle Detection Method</th>
<th>Preprocessing</th>
<th>Segmentation</th>
<th>Classification &amp; Recognition</th>
<th>Time Required</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Prediction-Based</td>
<td>Filtering using Kalman</td>
<td>Thresholding</td>
<td>Knowledge based</td>
<td>10-15 min.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Histogram equalisation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>Cellular automata &amp; neural network</td>
<td>Winer filering, laplace</td>
<td>Heuristic method for edge</td>
<td>Wash &amp; Hardmard Transform</td>
<td>8-10 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>operater for edge</td>
<td>detection &amp; segmentation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Region growing</td>
<td>Adaptive mean filtering</td>
<td>Quadtree decomposition</td>
<td>Merphological and functions</td>
<td>8-10 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>noise red. Edge detection</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Watershed segmentation</td>
<td>Median filtering</td>
<td>Split &amp; merge</td>
<td>Statistical moment based</td>
<td>7-8 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>image sharpening gradient</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Hough transform</td>
<td>Median filtering,</td>
<td>Statistical moments</td>
<td>Shape description</td>
<td>6 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>histogram equalization</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Homogenous region growing mean filter</td>
<td>HRGMF filter, edge</td>
<td>Optimal thresholding</td>
<td>Mathamatical Marpholocical</td>
<td>4 min</td>
</tr>
<tr>
<td></td>
<td></td>
<td>detection, filling</td>
<td></td>
<td>functions</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.5: Objective Analysis:

<table>
<thead>
<tr>
<th></th>
<th>Input Image</th>
<th>Output image</th>
</tr>
</thead>
<tbody>
<tr>
<td>MSE</td>
<td>1.9428</td>
<td>1.7495</td>
</tr>
<tr>
<td>PSNR</td>
<td>57.0444</td>
<td>63.3472</td>
</tr>
<tr>
<td>SNR</td>
<td>4.6596</td>
<td>3.2124</td>
</tr>
</tbody>
</table>
Some sample (patient’s) images are

Recognised By Algorithm

Recognised By Doctor

Recognised By Algorithm

Recognised By Doctor

Recognised By Algorithm

Recognised By Doctor

Our algorithm works with few predefined thresholds (e.g. at ovary estimation) which depend on type of ultrasonic device. If images obtained from another type of ultrasonic device are going to be tested, then a calibration of the required thresholds must be done. It is time consuming. The estimated ovary is sometimes too big, which can cause misidentification of many dark regions, very similar to follicles (by their shape, size etc.), but actually lying outside the boundary of the real ovary. Optimal threshold method used for the sub image segmentation gives normally good results, but in some ultrasound images of the ovary it causes merging of regions (threshold
too low). For normal follicles it is a sufficient algorithm & the results are up to 70 % we are experimenting with this to obtain these results up to 100 %.

Hence, we can conclude that with our algorithm, cost and time of processing of an image gets reduced and it can be proved subjectively as well as objectively.

Case 3: Processing of ultrasound image sequences for Quantitative analysis of fetal movements

One of the most significant advances provided by ultrasound is the potential it offers to examine the spatial and temporal characteristics of the movement of fetuses in their natural environment. The study of the spatial and temporal characteristics of fetal movement could significantly improve our understanding of neonatal sensorimotor functioning and the evolution of congenital motor disabilities [21]

In investigation of fetal movements the following organs are usually involved: trunk, arms, head, neck, breast, heart, eyes and mouth. Movement characteristics such as the force quality are important aspects of normal fetal movement strategies and may prove useful in early detection of fetal distress or pathology [21]. Today, no medical devices are available that can give an accurate and automatic movement measures of separate different organs. Medical device that are available can only give indication of global well-being and movement of different organs, can not be separated and measured. The most accurate and detailed information can be gathered by the use of a real-time ultrasound imaging systems. Physicians who are specialists in ultrasound monitoring can view the fetal motion and determine status of its neurological development. However, in most of the visual examination tests, the precise value of the movement kinematics parameters of fetal organs can not be obtained, rather they are described qualitatively by terms such as fast, slow, forceful, etc. Only recently, attempts were made to quantitatively measure the fetal angular velocity of the shoulder joint using real-time US images. These attempts were carried out through the use of special measuring equipment that is handled manually. Such a measuring process requires significant efforts and time due to the numerous amounts of frames of the images in the ultrasound video sequences.

Main Problems in Target Tracking in Ultrasound Images

Tracking and measuring the movement of fetal organs on ultrasound images requires the following problems:
• Image calibration and noise suppression;
• Target object location and tracking in cluttered background;
• Fast and accurate image geometrical transformation to allow for image variations in the process of movement and imaging.

The main sources of noise that may cause the target tracking failures are:

• Periodic noise due to imperfections is the VCR system;
• Speckle noise generated by the US imaging system.

The main obstacles for the reliable organ tracking are:

• The target organ is camouflaged by other organs in the field of view;
• Images are spatially very inhomogeneous;
• The target image changes considerably in the video sequence.

Image calibration techniques

Image calibration and de-noising techniques implemented in the system include:

1. Filtering Periodic Noise

The characteristic feature of periodic noise is that it has in its Fourier spectrum only a few components. A filter has been developed that automatically detects and then removes the noise spectral components thus producing periodic noise free images

2. Filtering Speckle Noise

US images suffer from a specific type of acoustic noise called speckle noise that can be observed as granular structure. Ultrasonic speckles, like similar phenomena encountered in laser and microwave radar imaging are the result of a coherent interference effect caused by the scattering of the ultrasonic beam from microscopic tissue in-homogeneities. A filter has been designed that suppresses the speckles noise efficiently, while preserving image edges and transient structures. The filter characterizations are the following:
• The filter works in a running window and is local adaptive;
• The filter works in the domain of Discrete Cosine Transform and nonlinearily transforms local DCT spectral coefficients to obtain an estimate for the central pixel of the window [21];
• The filter is based on the signal dependent noise model of the speckle noise.

Figure 4.7.1: Original Image with speckle noise  Figure 4.7.2: 7×7 Adaptive Filtered Image

Figure 4.7: Analysis of Fetal Movements

Organ Tracking Techniques

Organ tracking techniques include optimal adaptive correlator, image homogenization, image geometrical transforms and target coordinate measurement with sub-pixel resolution.

1. Optimal Adaptive Correlator

In order to secure the high organ tracking reliability we use, to determine the organ coordinates in the US image sequence, the optimal adaptive correlator [21]. The optimal adaptive correlator has the following advantages:

• It minimizes anomalous localization errors due to false identification of the target object with one of the background objects;
• It is adaptive to cluttered background.

Experimental tests have confirmed the superiority of the optimal adaptive correlator to conventional localization methods in terms of the localization reliability
2. Image Homogenization

To further improve the organ tracking reliability, an image homogenization procedure has been implemented that compensates to a certain degree image inhomogeneity by means of equalizing image local mean and local variance in a running window of the target object size.

Tracking with sub-pixel accuracy

The target coordinates are estimated from position of the signal highest peak at the output of the Optimal Adaptive Correlator. In order to achieve the sub-pixel localization accuracy, fast discrete sinc-interpolation [21, 22] of the correlator output signal has been implemented, the interpolation being carried out in a small region surrounding the main correlation peak.

Fast and Accurate Geometrical Transformation

In order to measure rotation angle of the organ in the video sequence, a fast accurate geometrical transform algorithm has been suggested. The algorithm has the following advantages:

- The algorithm is applicable for an arbitrary geometrical transform;
• The image transformation accuracy is that of the discrete sinc-interpolation [21, 22]

If the same transformation has to be applied many times with different mapping parameters to the same input image, as is the case of image rotation for the determination of rotation angle, the computational complexity is the same as that of the transformation with nearest-neighbor interpolation.

![Image of Fast Image Geometrical Transformation with Sinc-Interpolation]

**Figure 4.9: Fast image geometrical transformation with Sinc-interpolation**

**Tracking Technology**

The developed tracking techniques illustrated in Fig.4.9. The graphical user interface with a flexible organ marking technique has been designed to permit the user to visually analyze the ultrasound image sequence, to select and mark the fetal organs whose movements are then automatically measured and to observe the parameters of movement (location shift and rotation velocities) plotted in graphs. Once the organ target image has been prepared for the first frame, the target image is then prepared automatically for all the frames in the sequence. The scene image in which the target has to be searched is automatically prepared from the entire image frame. This minimizes the searching area which allows to additionally reduce the probability of localization errors and to accelerate the processing.
Case study 4: Detection of Cleft

Consider the following image is the face of the fetus. This is normal fetus for normal there is no problem, but if there is abnormality in the face like cleft, then we wants to see where is the actual site on the face. For this case, we use our technique to select and enhance particular object from an image. We can see abnormality in the face immediately. Here, our area of interest is to see weather there is an abnormality in lips or not. For this, we can choose the area of interest and zoom it and the results in x or y direction. Here, firstly the noise gets removed with the adaptive filtering and particular area of interest i.e. lips can be zoomed instead of whole image.
Case Study 5: Detection of defects in fetus spine

The following figure shows the spine of the fetus. Normally it is seen. But if there is abnormality in spinal cord, then it will not seen properly. To detect where abnormality is there, we can rotate that image and apply a magnification factor to detect that defect.

In above figure, we use rotation technique, in this we give image to be rotated and the angle of rotation. The Radon transform is used [12]. It will compute projections in a particular direction from the center of axis. Projections can be computed along any direction [13]. In general the Radon transform of $f(x,y)$ is the line integral of $f$ parallel to the $y$-axis

$$R_{\theta}(x') = \int f(x' \cos \theta - y' \sin \theta, x' \sin \theta + y' \cos \theta) dy'$$

where

$$[x', y'] = [\cos \theta \sin \theta, -\sin \theta \cos \theta][x, y]$$
References

2  A.M. Eskicioglu, “Image Quality and Their Measures and Their Performances”, IEEE Vol.43, December 1995