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Sonographic Image Quality Enhancement And Assessment Using Segmentation Technique

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Abstract—
The project includes the enhancement of sonographic image quality. Input would be from the database provided by the doctors and these database would be analyzed on the basis of parameters i.e receiving operating characteristic, detectability index,Kullback-Leibler divergence,signal to noise ratio,Monte carlo evaluation cellular automata algorithm.The cellular automata algorithm is used to enhance the quality of sonographic image which will help the doctor to predict that image. We will established relationship between image quality properties of developed system in order to predict the ideal performance. We will compare our result with the previous work done on sonographic image quality.
Keywords— Ultrasound Imaging,detectability,observer analysis, Image quality

I. INTRODUCTION

Image enhancement is the process on images to improve their appearance to human viewers or to enhance the performance of other image processing system. Processing of image in the presence of noise is one of the most common problems in this area.

The edge detection is another essential task in image processing. In processing of biological or medical images, the edge study becomes very important. But in general, we can detect an edge form an image very well if it is less affected by noise. For all cases like pattern recognition, object identification or segmentation noise must be reduced to get better result. So noise reduction is important issue before processing the image. Image processing using CA is a new e approach to the researchers.

IMAGING systems are devices that transport information from objects being examined to observers of the image who make decisions. Wagner approached the assessment of data quality by first partitioning the image formation process into *acquisition* and *display* stages . The sonographic acquisition stage, where patient information is recorded as radio-frequency(RF) echo signals, is governed by instrumentation variables including pulse transmission and echo reception properties up to and including beamforming. The sonographic display stage includes any postsummation data filtering, envelope detection, scan conversion, and gray-scale mapping leading to final B-mode presentation. Signal to noise ratio equals the detectability index found from the area under the receiver operating characteristic (ROC) curve[1]

II. RELATED WORK

A. *Medical Imaging*

The physical sensitivity of a medical imaging system is defined as the square of the output signal-to-noise ratio per unit of radiation to the patient, or the information/radiation ratio. This sensitivity is analyzed at two stages: the radiation detection stage, and the image display stage. The signal-to-noise ratio (SNR) of the detection stage is a physical measure of the statistical quality of the raw detected data in the light of the imaging task to be performed. As such it is independent of any software or image processing algorithms which belong properly to the display stage. The fundamental SNR approach is applied to a wide variety of medical imaging applications and measured SNR values for signal detection at a given radiation exposure level are compared to the optimal values allowed by nature. It is found that the engineering falls short of the natural limitations by an inefficiency of about a factor two for most of the individual radiologic system components, allowing for great savings in the exposure required for a given imaging performance when the entire system is optimized. The display of the detected information is evaluated from the point of view of observer efficiency, the fraction of the displayed information that a human observer actually extracts. It has been found that the human observer is able to extract more than 50 percent of the displayed information in simple images when they are presented such that the noise is easily visible; otherwise, the internal noise sources of the observer degrade observer efficiency for lesion detection to much lower values.

Methods for optimizing both the detection and both the detection and the display of medical image information are presented in terms of the information/radiation ratio together with brief descriptions of the measurement methodology required to assess the images[2].

Linear equations for modeling echo signals from shift-variant systems forming ultrasonic B-mode, Doppler, and strain images are analyzed and extended. The approach is based on a solution to the homogeneous wave equation for random inhomogeneous media. When the system is shift-variant, the spatial sensitivity function—defined as a spatial weighting function that determines the scattering volume for a fixed point of time—has advantages over the point-spread function traditionally used to analyze ultrasound systems. Spatial sensitivity functions are necessary for determining statistical moments in the context of rigorous image quality assessment, and they are time reversed copies of point-spread functions for shift variant systems. A criterion is proposed to assess the validity of a local shift-invariance assumption. The analysis reveals realistic situations in which in-phase signals are correlated to the corresponding quadrature signals, which has strong implications for assessing lesion detectability. The analysis connects several well-known approaches to modeling ultrasonic echo signal[3].

A principles task based on approach to the design of medical ultrasonic imaging systems for breast lesion discrimination is described. This study explores a new approximation to the ideal Bayesian observer strategy that allows for object heterogeneity. The new method, called iterative Wiener filtering, is implemented using echo data simulations and a phantom study. We studied five lesion features closely associated with visual discrimination for clinical diagnosis. A series of human observer measurements for the same image data allowed us to quantitatively compare alternative beamforming strategies through measurements of visual discrimination efficiency. Employing the Smith–Wagner model observer, we were able to breakdown efficiency estimates and identify the processing stage at which performance losses occur. The methods were implemented using a commercial scanner and a cyst phantom to explore development of spatial filters for systems with shift-variant impulse response functions. [4].

Under a contract with the National Cancer Institute, we have developed a research interface to an ultrasound system. This ultrasound research interface (URI) is an optional feature providing several basic capabilities not normally available on a clinical scanner. The URI can store high-quality beamformed radio-frequency data to file for off-line processing. Also, through an integrated user interface, the user is provided additional control over the Bmode receive aperture and color flow ensemble size. A third major capability is the ability to record and playback macro files. In this paper, we describe the URI and illustrate its use on three research examples: elastography, computed tomography, and spatial compounding[5]

B. *Cellular Automata Algorithm*

In the proposed work Cellular Automata (CA) has been used for noise filtering. Hence for the sake of completeness a brief overview of CA is provided in this section. Although the concept was proposed almost five decades back by John Von Neumann, but in the last two decades, researchers of various fields became interested to use the concept. CA has wide range of applications in the field of pseudo random sequence generation, error correcting code, VLSI circuit testing and image processing.

CA consists of a large number of relatively simple individual units, or ―cells , which are connected only locally, without the existence of a central control in the system. Each cell is a simple finite automaton that repeatedly updates its own state, where the new cell state depends on the cell's current state and those of its local neighbors. However, despite the limited functionality of each individual cell, and the interactions being restricted to local neighbors only, the system as a whole is capable of producing intricate patterns, and even of performing complicated computations. In this way, they form an alternative model of computation, in which processing of information is done in a distributed and highly parallel manner. Because of these properties, CA has been used extensively to study complex systems in nature, such as fluid flow in physics or pattern formation in biology, and also to study image processing[6,7]

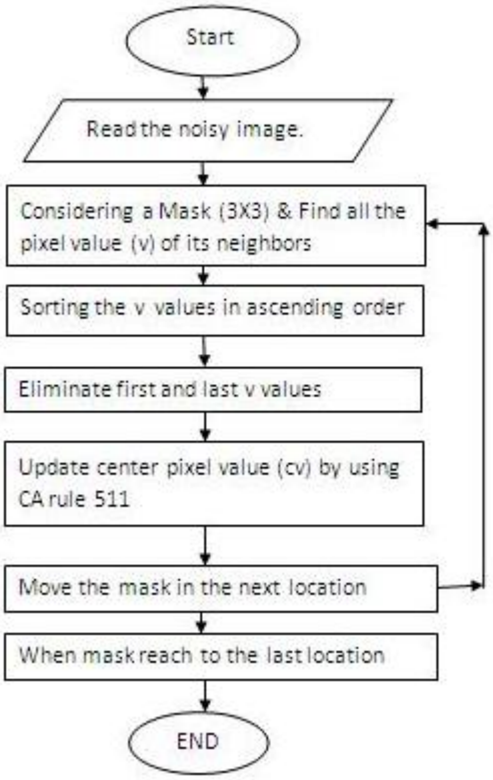

Fig. 1 Flowchart of CA Algorithm

Step 1: Consider a noisy image with m×n matrix of 8 bit gray scale image and 3×3 masks

Step 2: Consider CA of r=2 and center pixel is considered as cv. So total neighbor n=8 and total cell of CA is 9

Step 3: Store the pixel value in vi for all i=1 to 9, which belong to the considering mask area

Step 4: Arrange vi in ascending order

Step 5: Eliminate minimum and maximum vi values and

Calculate avg =Σ vi /k, for all i = 2 to k and k=n-1

Step 6: Center pixel value is updated by using CA rule 511 **Step 7:** Move the mask in the next location and go to step 3 until it reach to the last location of noisy image

Step 8: End

C. *Histogram Equilization*

Histogram equalization is a method in image processing of contrast adjustment using the image's histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.In scientific imaging where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the small signal to noise ratio usually hampers visual detection.Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images that user would apply false-color to. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to 8-bit image displayed with 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images.There are two ways to think about and implement histogram equalization, either as image change or as palette change. The operation can be expressed as P(M(I)) where I is the original image, M is histogram equalization mapping operation and P is a palette. If we define a new palette as P'=P(M) and leave image I unchanged then histogram equalization is implemented as palette change. On the other hand if palette P remains unchanged and image is modified to I'=M(I) then the implementation is by image change. In most cases palette change is better as it preserves the original data. Generalizations of this method use multiple histograms to emphasize local contrast, rather than overall contrast. Examples of such methods include adaptive histogram equalization and contrast limiting adaptive histogram equalization or CLAHE.Histogram equalization also seems to be used in biological neural networks so as to maximize the output firing rate of the neuron as a function of the input statistics. This has been proved in particular in the fly

HYPERLINK "http://en.wikipedia.org/wiki/Retina" retina. Histogram equalization is a specific case of the more general class of histogram remapping methods. These methods seek to adjust the image to make it easier to analyze or improve visual quality (e.g., retinex).

D. *Image Quality Assessment*

The presentation method for assessment of image quality combines elements of the simultaneous double stimulus and the double stimulus continuous quality scale (DSCQS) method. for continuous evaluation (SDSCE) method.For reference, it may be called the simultaneous stimulus relative quality scale (SSRQS) method.As with the SDSCE method, each trial will involve a split-screen presentation of material from two movies.One of the movie sources will be the reference (i.e., source movie), while the other is the test movie. The reference could be a conventional setup or the setup to compare against, and the test movie is the method under investigation. For both methods the parameters are optimized according to the diagnostic performance of the recording medium. Unlike the SDSCE method, observers will be unaware of the scanner conditions represented by the two members of the movie pair and the left-right placement of the movies are randomized. As with the DSCQS method, a test session comprises a number of presentations, each with a single observer.Unlike the DSCQS method where the assessor only observes the stimulus two times and rates each stimuli, the assessor is free to observe the stimuli until a mental measure of relative quality associated with the stimulus is obtained. Figure 4a shows a basic test cell illustrating the presentation structure of reference and test material. Reference and test movies are displayed as matching pairs side-by-side with random left-right placement. Stimuli are visualized in a palindromic (playback may be reversed in time) display fashion in order to minimize discontinuity at the joints.

E. *Fuzzy C-Means Clustering*

Data clustering is the process of dividing data elements into classes or clusters so that items in the same class are as similar as possible, and items in different classes are as dissimilar as possible. Depending on the nature of the data and the purpose for which clustering is being used,different measures of similarity may be used to place items into classes, where the similarity measure controls how the clusters are formed. In contradistinction to hard clustering, in fuzzy clustering each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to just one cluster (Löster, 2012). Thus, points on the edge of a cluster, may be in the cluster to a lesser degree than points in the center of cluster.

fuzzy logic theory applied in cluster analysis includes Fuzzy logic becomes more and more important in modern science. It is widely used: from data analysis and forecasting to complex control systems. In this article we consider clustering based on fuzzy logic, named Fuzzy Clustering. Clustering involves the task of dividing data points into homogeneous classes or clusters so that items in the same class are as similar as possible and items in different classes are as dissimilar as possible. In hard clustering, data is divided into crisp clusters, where each data point belongs to exactly one cluster. In fuzzy clustering, the data points can belong to more than one cluster, and associated with each of the points are membership grades which indicate the degree to which the data points belong to the different clusters. There are many methods of Fuzzy Clustering nowadays.

III. PROPOSED WORK

A. *Objective*

The objective of this project is the reduction in the noise of sonographic images, enhance the contrast in the images and smoothing of images by using the segmentation technique and cellular automata algorithm i.e.

- The noise of the image is reduced by using the cellular automata algorithm.
- The contrast in the image is enhanced by using various mathematical operations.
- The smoothing and sharpness is enhanced by using segmentation.
- Evaluate the image and find out its quality(quality in terms of image sharpness and SNR)

B. WORK PROPOSED ON EACH OBJECTIVE

The noise of the image is reduced by using the cellular automata algorithm. The contrast in the image is enhanced by using various mathematical operations. The smoothing and sharpness is enhanced by using segmentation.

Histogram equalization is a technique for adjusting image intensities to enhance contrast .

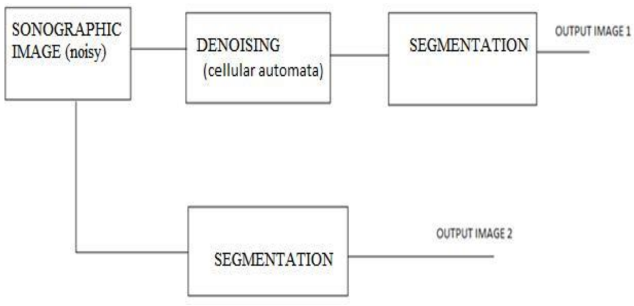

Fig. 1 Block Diagram for Obtaining Quality Of Image

In this block diagram, there are four blocks. The first block represents the sonographic image which is obtained from the ultrasound device.The sonographic image is noisy so that for reduce this noise reduction we perform the segmentation process on that image.so we obtained the output image 2.For reduce the noise in sonographic image,we will do denoising by using cellular automata so that quality of that image will be improved.After denoising the segmentation process is done and we obtain the output image 1.These two images are compared and we will decide which image is more clear,obivious and smooth.In this project we compare the peak signal to noise ratio.The output image 1 is more smooth and clear than the output image 2.So that the quality will be improved by using cellular automata algorithm.

- Collection of some sonographic images.
- Sonographic images of fetus,abdomen,liver,spleen kidney ,pancreas,spine.
- Implementation of Histogram based image enhancement.
- Enhancement of the input image in order to improve the image contrast.
- Implementation of Laplacian based image enhancement techniques.
- Result optimization
- Result evaluation and comparison

IV. EXPERIMENTAL RESULT

The use of statistical decision theory to obtain the ideal observer SNR for a given lesion detection task serves as the basis of a rigorous solution to the problem of assessing the sensitivity of medical imaging systems. It allows us to calculate the ideal performance, that is, the best performance allowed by nature with a given level of radiation exposure to the patient.The experimental result shows that we obtain the sonographic image of fetus,we consider many medical images like liver,kidney spine and obtain the more improved image.

The objective approach to assessment of image quality utilizes task performance as the figure of merit for determining medical image quality. In this way, all components of the imaging chain—from the formation of contrast in the body to display and reader effects—can be investigated for their influence on diagnostic accuracy. For analyzing imaging systems, it can be illuminating to consider the performance of the Bayesian ideal observer , often referred to simply as the ideal observer.

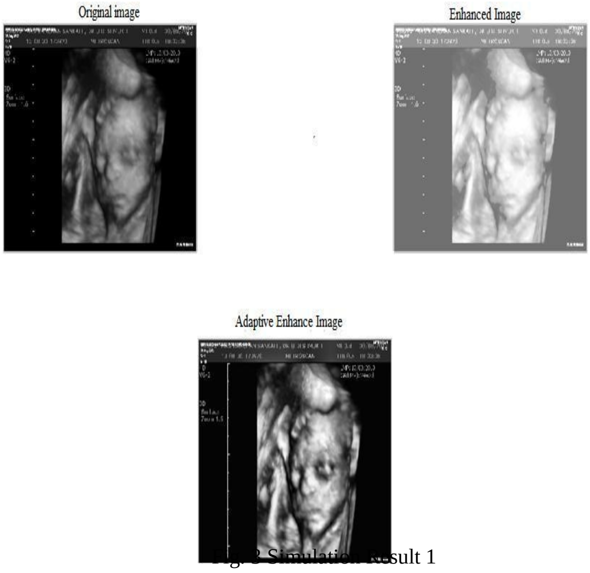

Fig. 3 Simulation result 1

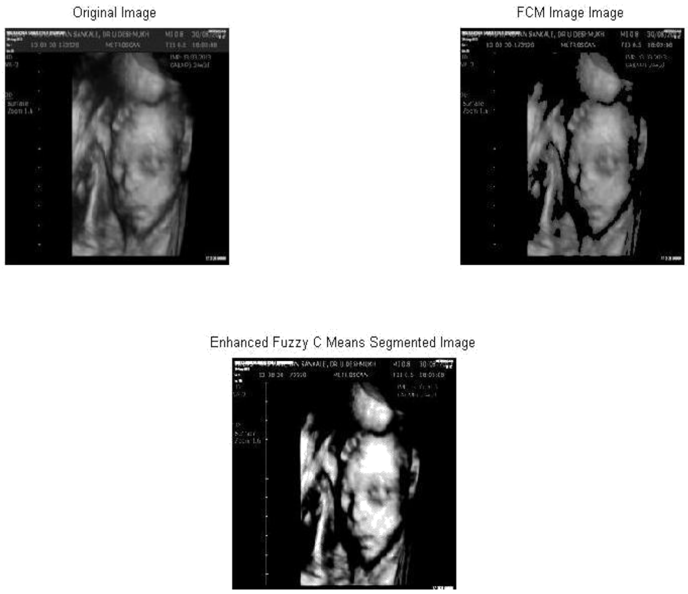

Fig. 4 Simulation Result 2

Fig.3 shows simulation result1 in which we obtained the enhanced image and adaptive enhanced image by using hist equalization and adaptive hist equalization function .Fig.4 shows simulation result2 in which we obtained FuzzyC Means image and Fuzzy C Means segmented image in that we detect background part and remove foreground part. When pixel value is greater than threshold value we obtained foreground object and when pixel value is less than threshold value we obtained background object.

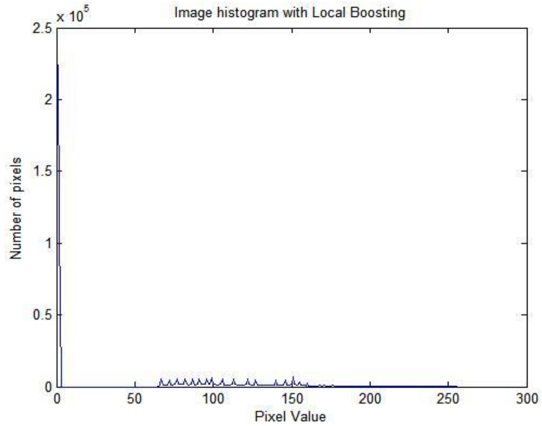

Fig. 5 Graph of Image Histogram with Local boosting

Fig.5 shows graph of image histogram with Local boosting which is plotted between number of pixel and pixel values.This is not the smooth graph. For obtaining more smooth graph we use laplacian filter which is shown in Fig.6.By observing Fig.6 it is seen that their is the smooth graph and reducing the local boosting.

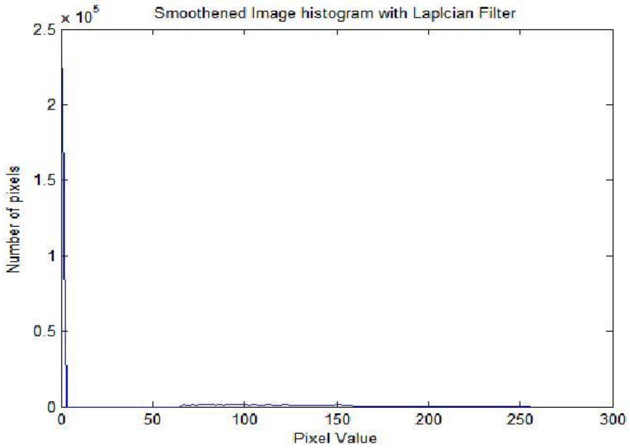

Fig. 6 Graph of Image Histogram with Lapalacian Filter

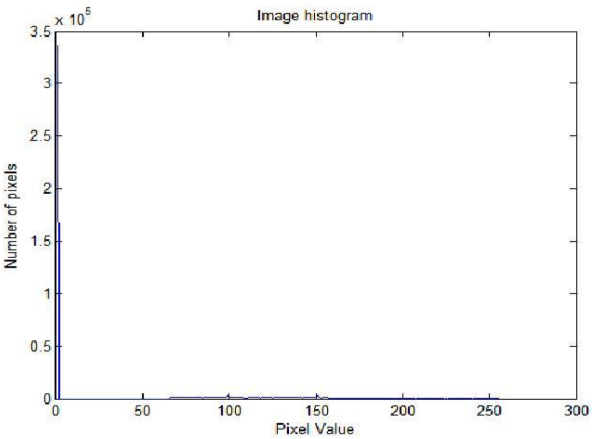

Fig. 7 Graph of Image Histogram

By combining histogram as shnown in Fig.5 and Fig.6 we obtained the graph of image histogram as shown in Fig.7. This is the smooth graph for obtaining more enhanced image .

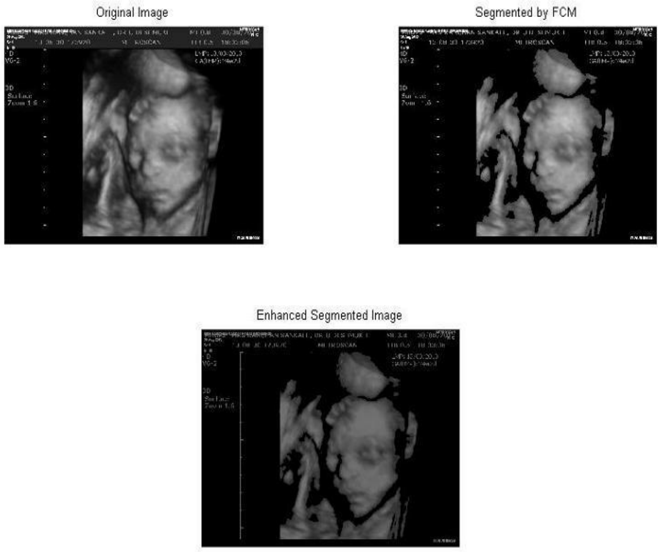

Fig. 8 Simulation Result 3

Fig.8 shows simulation result 3 which shows the segmented image and enhanced segmented image which is the output of this paper having more signal to noise ratio than other results in the paper.

V. CONCLUSIONS

The sonographic image is improved by reducing the noise. It is shown that the noise removal schemes based on CA provides better results compared to existing schemes with respect to PSNR. But it is found that the output of CA-based image noise reduction module has to be passed through a high-level image processing unit to produce equations of the lines and edge co-ordinates. In our two approaches it has been found that the result depends on the order of CA. But there will be some trade-off between the blurring of resulted image and order of CA.

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