disease. This study mainly focuses on reducing noise and apply a better segmentation technique for an improved diagnosis from the images.

3.2 Filtering Methods

Five different varieties of filters were applied over these images to remove varieties of noise. Each of these filters have a capacity to remove a different kind of noise present in the image.

3.2.1 Mean (Average) Filter

Mean filter is a low pass filter that smoothens the image by reducing the variation of intensity between each pixel and its neighbour. The underlying idea in this type of filter is that every pixel in the image is an average across its neighbourhood.
Let (x, y) be the integer coordinates with M-1>=x>=0 and N-1>=y>=0, f(x, y) be the input image and g(x, y) be the filtered image, then both f and g images are of the size MXN and g(x, y) is given by Eq. (1) as,

$$g(x, y) = \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s,t) f(x+s, y+t) \qquad (1)$$

3.2.2 Median Filter

Median filter is a non-linear filtering technique that attempts to preserve the edges of an image while removing the noise. A mask slides through every pixel of the image and calculates the median of the neighbourhood pixels. It is particularly effective when speckle noise and salt and pepper noise interfere with the image. This Filter is more robust than mean filter.

3.2.3 Wiener Filter

Wiener filter computes a statistical estimate of desired target by a linear time-invariant. It assumes the image pixels, noise spectra and additive noise and filters the noise pixels. It serves as better method to minimize the MSE between the desired image and the estimated image. These filters are usually applied in frequency domain and are comparatively slow.
Applying Discrete Fourier Transform on a degraded image X(n, m), it gives rise to X(u, v). The original image represented as S(u, v) is then estimated by computing the product of the transformed image with that of Wiener filter given by G(u, v) in Eq. (2) as,

$$S(u, v) = X(u, v)*G(u, v) \qquad (2)$$

3.2.4 Gaussian Filter

Gaussian filter is a low pass filter which smoothens an image and commonly used with edge detection. Gaussian filter transforms the input image by convolution of Gaussian function. Every pixel in the image is transformed using Gaussian distribution. Gaussian function in two dimensions is represented by Eq. (3) as,

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x^2+y^2}{2\sigma^2}} \qquad (3)$$

Where the distance from the origin to x-axis is represented by x and distance from the origin to y-axis is represented by y and σ represents the standard deviation of the Gaussian distribution.

3.2.5 NAFSM Filter

Noise Adaptive Fuzzy Switching Median Filter (NAFSM) was introduced by Kenny Kal Vin Toh, et al., [10] that reduces salt and pepper noise to a great extent. It is a combination filter of both simple adaptive median filter introduced by H. Ibrahim, et al., [13] and the fuzzy switching median filter introduced by K. K. V. Toh, et al., [14]. The adaptive behaviour of NAFSM filter enables it to enlarge the filtering window to the size of local noise density, allowing it to filter only the noise pixels and retain the rest of the pixels, thereby reducing the salt and pepper noise. This filter has given a vast difference in the accuracy when compared with the rest of the filters.

The dataset that contained 33 different subjects with different kinds of congenital diseases were filtered using mean (or average) filter, median filter, Wiener filter, Gaussian filter and the NAFSM filter. The Peak Signal to Noise Ratio is estimated in db for all the images and it was observed that NAFSM, a hybrid version of both adaptive median and fuzzy switching filters, has given the highest PSNR of all the five filters.

3.3 Segmentation methods

Image segmentation is an indispensable technique in image processing to spot the area of interest, especially in medical imaging to reason out the defect or malfunctioning of vital parts. It is the process of partitioning an image into a number of segments, so as to precisely locate the objects and their boundaries. Many techniques have been developed for image segmentation, depending on the application, but for congenital heart disease analysis, a familiar and most commonly used Threshold segmentation is applied. Another segmentation that is used in this study is the watershed segmentation. The filtered images taken from Non Adaptive Fuzzy Switching Method were given as input to this segmentation process and the output images were collected to further apply morphological operations. This paper holds only the filtered images and the segmented images to carry out further analysis over these congenital heart images.

3.3.1 Threshold Method

A non-parametric and unsupervised thresholding method was introduced by Nobuyuki Otsu in 1979 [4], where an optimum threshold is chosen using the discriminant criterion between the gray levels of the image. It is a simple process where it calculates from the zeroth a first order aggregate moments of the gray-level histogram. In this, an optimum threshold is being selected not based on the local property but on the global property of the histogram.

In this method, threshold is expected to minimize the intra-class variance, which is defined as a sum of weights of variances of two classes and is represented by Eq. (4),

$$\sigma_w^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(\mathrm{t}) \quad (4)$$

Where ω_0, ω_1 are probabilities of two different classes separated by a threshold t and $\sigma_0{}^2$, $\sigma_1{}^2$ are variances of these two classes.

3.3.2 Watershed Method

Conventional Watershed segmentation transformation is a commonly used segmentation method which is defined on gray scale images. It is basically a region based segmentation approach initially proposed by Digabel and Lantuejoul in 1977 [15] and was later enhanced by Li, et al., in 2003 [16]. NAFSM filtered cardiac MRI images are given as inputs to this watershed algorithm and the segmented images are taken as output images for further applying some morphological transformations.

Both threshold segmented images and watershed segmented images are taken as inputs to further analysis by applying morphological transformations to make the region of interest achieve more clarity for the doctor's decision to be more appropriate.

4 Experimental Results

The collected cardiac MRI images were given as inputs and were subjected to various filters and studied which filters were more suitable for the enhancement of images using a metric called PSNR. The PSNR for an image is computed as the ratio between maximum strength of the original signal to that of noise that disturbs its representation and is usually expressed in decibel scale. Often it is used to estimate the reconstructed images for their quality. Noise is referred to as the error introduced into the original signal through compression. PSNR approximates human perception of reconstructed quality, especially when compressed images are compared. Higher the value of PSNR better is the reconstruction quality. PSNR is a computational measure to find the quality of the image based on pixel difference between pixels between two images. The Signal to Noise Ratio (SNR) computes the quality of a recreated image when compared to that of the original image. The PSNR would be same as SNR when all pixel values are equal. The filtering techniques were applied and tested on Cardiac MRI images. Median Filter, Average Filter, Wiener Filter, Gaussian Filter and Noise Adaptive Fuzzy Switching Median (NAFSM) Filters were applied and NAFSM filter enhanced the MRI Cardiac Images. The comparison was made on Filtered Images for quality and depicted those enhanced images in the following Table-2. The comparison metric PSNR values for quality of the images were also mentioned in the last column of the Table-2. It is evident from the Table-2 that NAFSM filter has enhanced the Image quality compared to all other filter techniques. Next to the NAFSM filter, Gaussian filter proved to be good, which then followed by Wiener filter. The same was evident from the graph represented in Fig.1. Segmentation of Images was done using two methods Threshold and Watershed shown in Table-3 and performance evaluation was made using PSNR metric values shown in Table-4. It is found that the Threshold segmentation method was found to be good when compared with watershed segmentation. Fig.2 shows the comparison graph. The Tables are showing few MRI images results, but it was carried on all 33 images.

Table 2. Sample of 10 MRI filtered images with their respective PSNR values

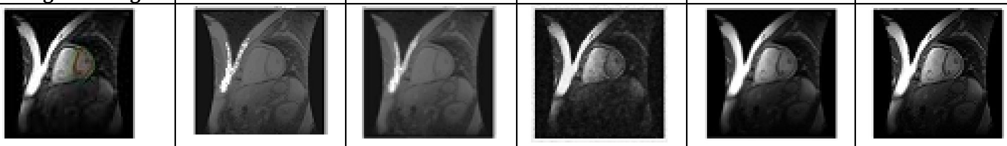
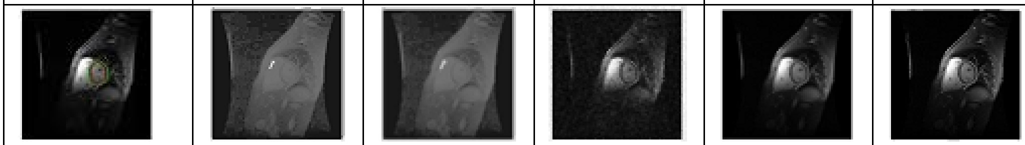
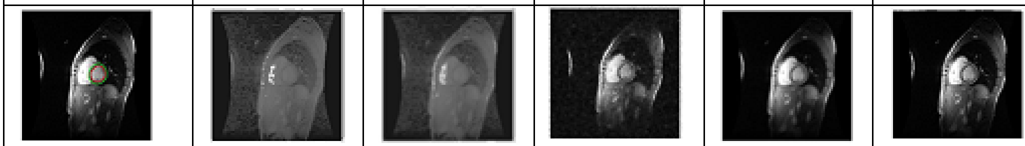
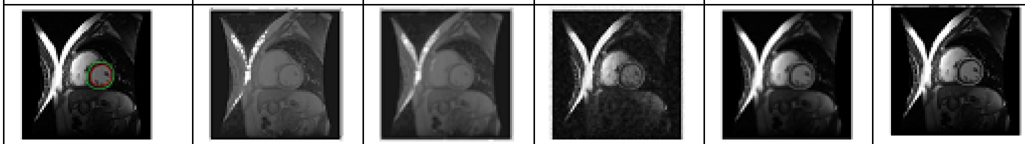
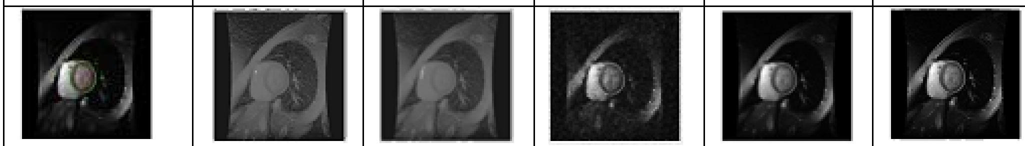
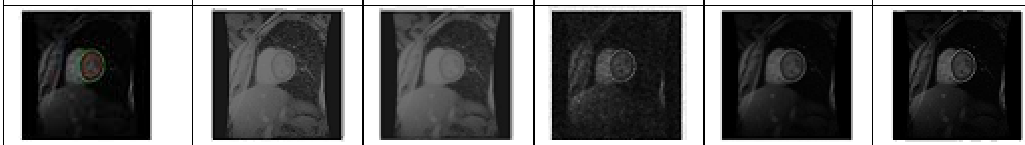
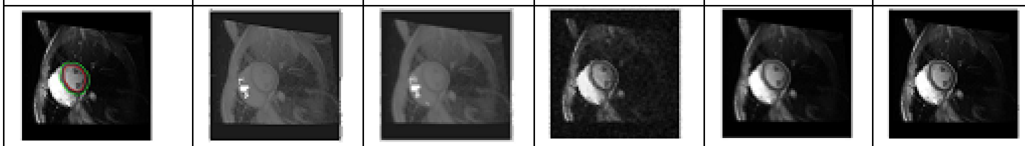
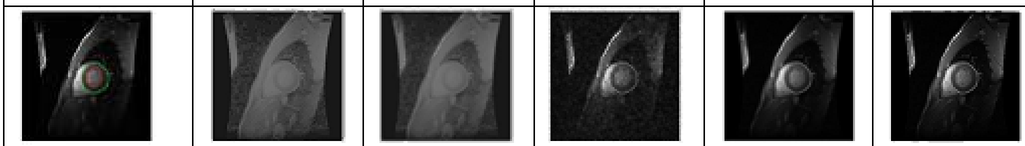
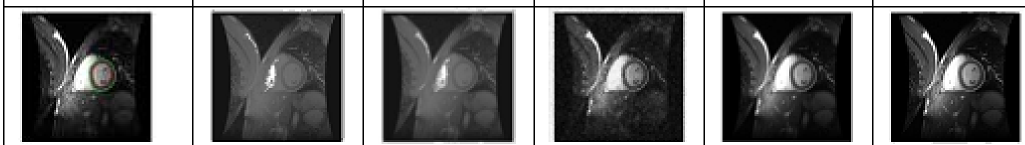
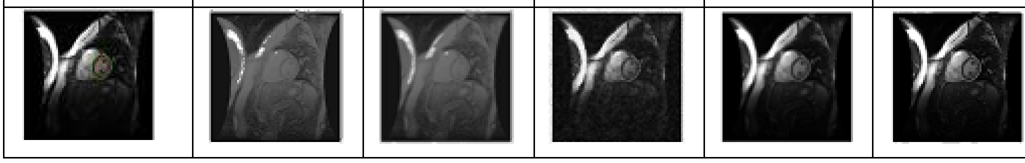
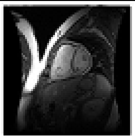
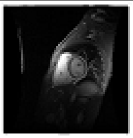
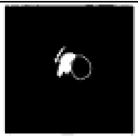
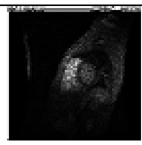
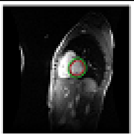
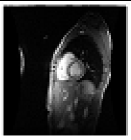
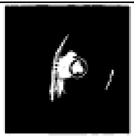
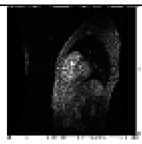
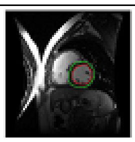
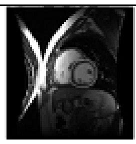
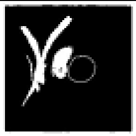
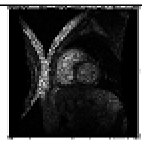
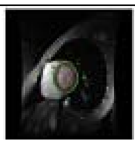
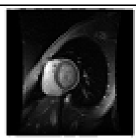
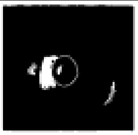
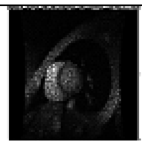
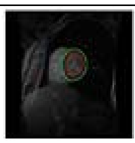
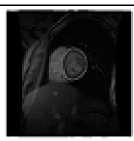
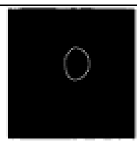
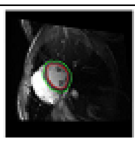
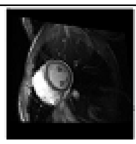
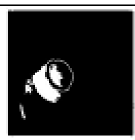
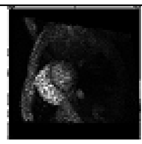
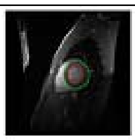
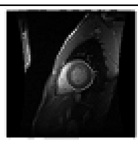
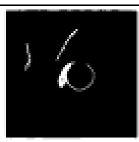
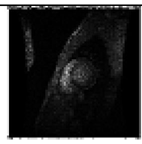
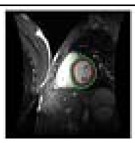
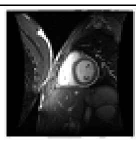
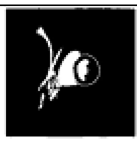
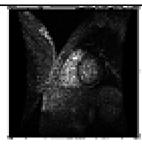
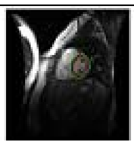
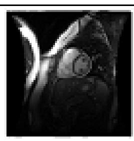
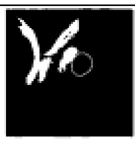
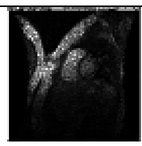
Original Image	Median filtered	Average filtered	Wiener filtered	Gaussian filtered	NAFSM filtered	PSNR
						med = 18.1394 avg = 17.6229 wien = 23.1523 Gauss = 23.2720 NAFSM = 28.9906
						med = 16.9278 avg = 16.4961 wien = 23.3653 Gauss = 23.6441 NAFSM = 29.0063
						med = 17.0316 avg = 16.6623 wien = 22.9988 Gauss = 23.1590 NAFSM = 26.5736
						med = 17.4943 avg = 17.0933 wien = 22.9889 Gauss = 23.0604 NAFSM = 27.9424
						med = 17.4991 avg = 16.9791 wien = 23.3346 Gauss = 23.6110 NAFSM = 26.5527
						med = 17.2458 avg = 16.7177 wien = 23.5411 Gauss = 23.7270 NAFSM = 26.8404
						med = 17.5475 avg = 17.0176 wien = 23.3279 Gauss = 23.6610 NAFSM = 30.1076
						med = 17.1683 avg = 16.6682 wien = 23.2778 Gauss = 23.4288 NAFSM = 27.2619
						med = 18.5658 avg = 17.9629 wien = 23.2871 Gauss = 23.4222 NAFSM = 28.0004
						med = 17.5281 avg = 17.1190 wien = 23.1601 Gauss = 23.5148 NAFSM = 28.7978

Table 3. Sample of 10 NAFSM filtered images being segmented using two different methods Threshold and Watershed Segmentation

Original Image	**NAFSM filtered Image**	**Threshold segmented Images**	**Watershed Segmented Images**	**PSNR**	
				Threshold	**Watershed**
				19.1818	14.2647
				21.3082	15.5509
				19.8675	14.1695
				19.9323	14.0255
				20.1542	14.7456
				22.9316	15.2529
				19.9094	14.7979
				21.3351	15.3704
				18.7359	14.3961
				20.0680	14.4714

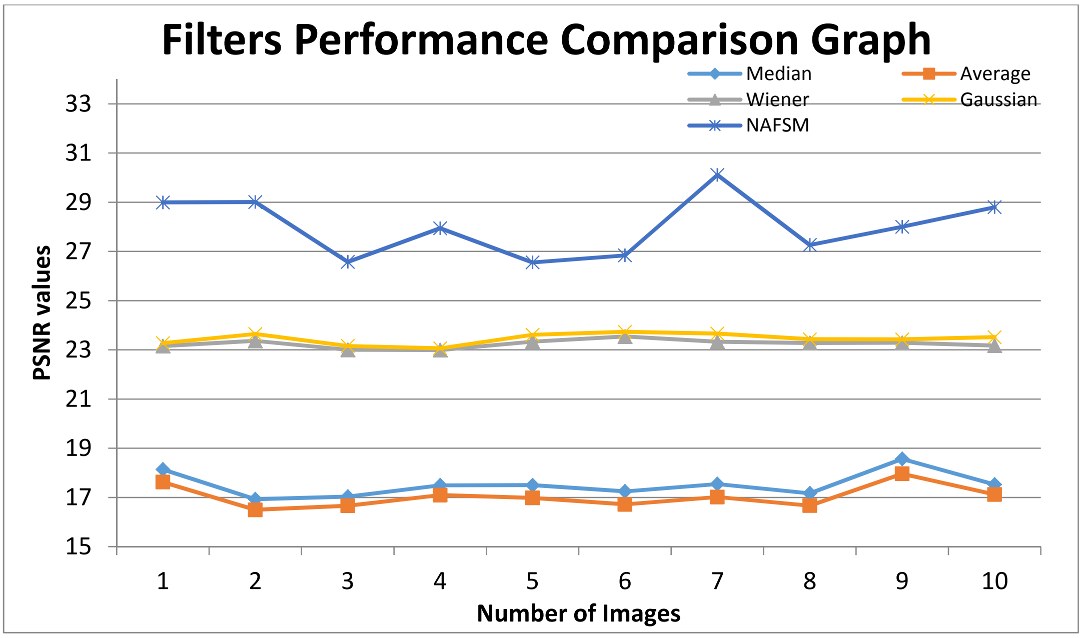


Fig.1: Performance based comparison of Filters on Images using PSNR metric

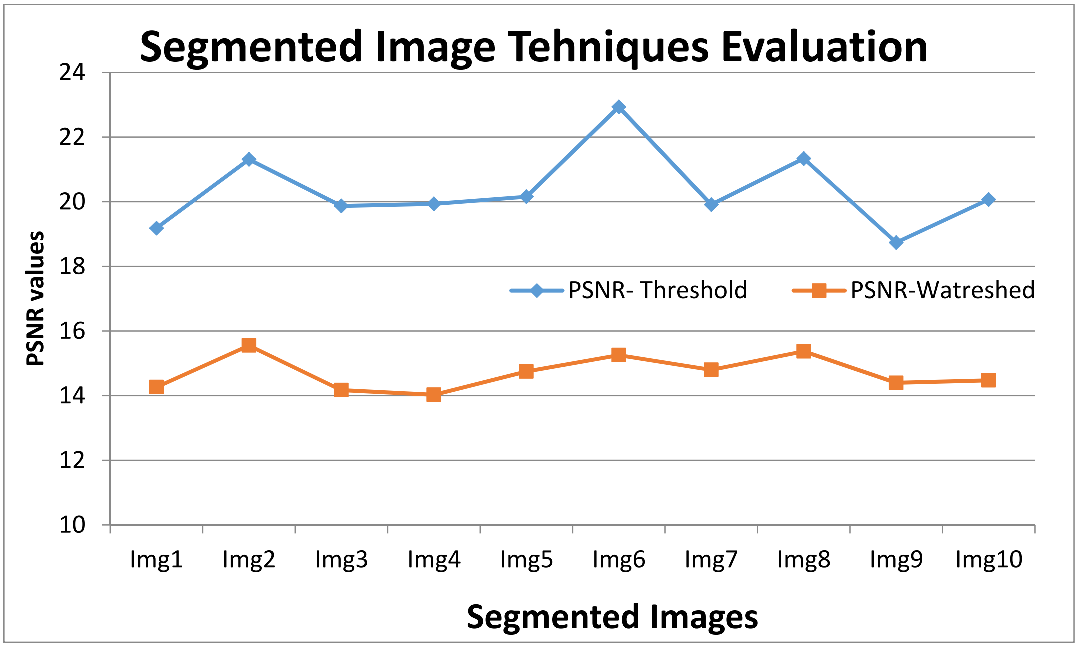


Fig.2: The Comparison graph of two segmentation methods

Table 4. The PSNR values of two segmentation methods

Segmented Images \ Metric	PSNR- Threshold	PSNR-Watershed
Img1	19.1818	14.2647
Img2	21.3082	15.5509
Img3	19.8675	14.1695
Img4	19.9323	14.0255
Img5	20.1542	14.7456
Img6	22.9316	15.2529
Img7	19.9094	14.7979
Img8	21.3351	15.3704
Img9	18.7359	14.3961
Img10	20.068	14.4714

5 Conclusions and Future work

In this paper, cardiac MR images from 33 subjects with heart ailments were pre-processed using five types of filters viz., Median filter, Mean Filter, Wiener filter, Gaussian filter and NAFSM filter. Their peak signal to noise ratios were found out and the Noise Adaptive Fuzzy Switching Median filter resulted in a better PSNR values than that of other filters. Mean filter and Median filter proved to be not suitable for enhancement of MRI images. Gaussian and wiener filters performance are almost same, but NAFSM filter outperforms all the filters in the enhancement of image quality. Two segmentation methods were carried on refined MRI images obtained by NAFSM filter and their performance evaluation was done and it is found that Threshold segmentation was good when compared to Watershed segmentation. Further we perform morphological operations to figure out the exact location of heart ailment in the next course of our research work.

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