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Super Resolution Of Mammograms For Breast Cancer Detection

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Abstract

Mammography has been the most popular method for the early detection of the breast cancer. Due to low contrast of mammograms typical diagnostic signs such as masses and micro calcification are difficult to detect. So to create a high resolution mammogram super resolution (SR) technique can be used. This technique will make a high resolution image from a series of low resolution images of the same scene. A novel algorithm with interpolation for super resolution reconstruction has been proposed here. It has taken a interpolation technique that preserves edges without introducing any artifact. This also avoids pixilation, over smoothing and blurring of images. In our method we have used denoising, deblurring and registration technique to improve the quality of low resolution images and fused them to produce a higher resolution image. The proposed algorithm is a hybrid of bilinear interpolation and FCBI method with edge detecting criteria.

Keywords: mammogram, interpolation, artifact, pixilation, smoothing, bilinear interpolation, FCBI method

1. Introduction

Breast cancer is the most leading type of cancer in women now. It is important to detect breast cancer in early stages. The most effective method is digital mammography. It is also important to reduce patients radiation exposure. It is found that a single mammogram produced at 226mAs can be produced by combining several low resolution mammograms having less radiation exposure at 169.5mAs. To improve the visibility of several features in the mammogram multi source super resolution is a promising algorithm that may be used. In the proposed approach a set of low resolution (LR) inputs are used to detect the cancerous tissues, from which a high resolution image is obtained. High Resolution (HR) images give better and accurate results for early detection of cancer in most of the cases. Our proposed approach may be used to reduce the radiation given to the patient.

2. Literature Survey

Iterative blind deconvolution has been used in proposed method for blurred image. Denoising is done using wiener filter and registration is done for the translated image, after these 3process done wavelet based image fusion. Finally proposed interpolation algorithm used to get the best result. Before that let us analyses the state of art of super resolution methods. In Super Resolution of Mammograms [1] algorithm combines statistical machine learning methods with the stochastic search to learn the mapping from low-resolution to high-resolution mammograms from a large dataset of training image pairs. Here there is no need of manual registration and we get high PSNR, MSSIE values. But here it may loss some information in super resolution image and speed is less. Fourier base multi frame in super resolution procedure can also be used. Efficient Fourier-Wavelet Super-Resolution [2] says that method first uses a fast Fourier-base multi frame image restoration to produce a sharp, yet noisy estimate of the high-resolution image. Then applies a space-variant nonlinear wavelet thresholding that addresses the non stationary inherent in resolution-enhanced fused images. It will reduce the memory requirements by applying algorithm in small tiles. It is useful only when we know the motion of the low resolution images. Frequency wise analysis is described in Phase-Adaptive Super resolution of Mammographic Images using Complex Wavelets [3] In this approach, the super resolution problem is formulated as a constrained optimization problem using a third-order Markov prior model, and adapts the priors based on the phase variations of the low-resolution mammographic images. This will improve the visibilities of nodules, boundaries and calcification. Here phase coherence is sensitive to noise and produce less structural details. In A novel super resolution reconstruction of low resolution images progressively using DCT& zonal filtering [4] the problem of creating high resolution image from the set of low resolution images are considered. At the encoder side low resolution images are considered they are affected by white Gaussian noise and motion blur. The low resolution images are compressed using 8 by 8block DCT and noise is filtered using zonal filter. Multi frame fusion scheme is used to get the single image. At the decoder side high resolution image is obtained using adaptive interpolation algorithm. But this one is not also accurate since we are considering the 8 by 8 blocks some local properties may loss. In A Novel and Efficient Lifting Scheme based Super Resolution Reconstruction for Early Detection of Cancer in Low Resolution Mammogram Images [5] some modification has done. Lifting wavelet based adaptive interpolation algorithm is proposed here. Daubechies (D4) lifting schemes to decompose low resolution mammogram images into multilevel scale and wavelet coefficients. Then proposed novel soft thresholding technique is used to remove the noisy coefficients, by fixing optimum threshold value. In order to obtain an image of higher resolution adaptive interpolation is applied.

3. Proposed System

Collected data set from MIAS database and hospital. It is having normal, begin, malignant cases also have the dataset from hospital which are affected by cancer. The data set are mammograms in JPEG format which is having 492x595. System architecture is shown in figure 1.

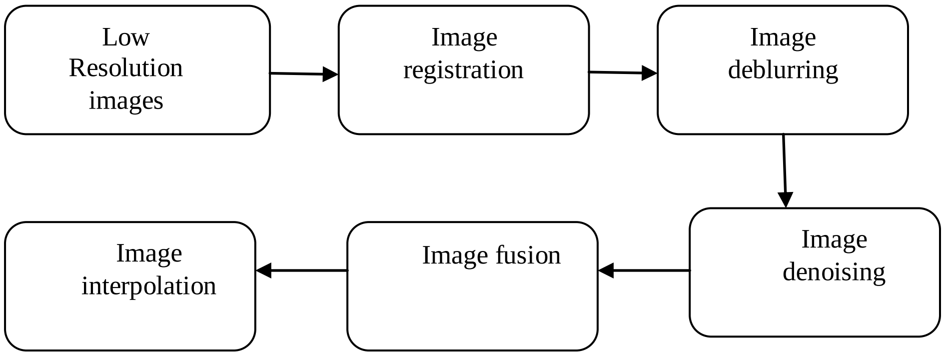


Fig 1: architectural diagram

Three low resolution set of images have been used. One is noisy, other is blurred and the third one is shifted version of mammogram. Adaptive Wiener filter method used for denoising the noisy image. The blurred image is processed using Iterative Richardson-Lucy Algorithm; finally the shifted image is registered using a modified phase correlation based on Fast Fourier Transform proposed by Fourier Mellin and DeCastro. The fusion of these 3 images is performed using wavelet based fusion using maximum frequency fusion rule. To increase the spatial resolution a new algorithm has been proposed based on edge feature of image. By considering the edge feature the structural details in the mammogram get enhanced.

3.1 Proposed Algorithm

Considering the edge feature it has been proposed a hybrid of two interpolation method. One is linear interpolation method which is used in the non edge detected areas and other one is adaptive interpolation method. FCBI is a strong adaptive interpolation method which is used in the edge detected areas. Bilinear interpolation is a very simple type interpolation technique. It takes four points that are closest to the diagonal corners and averages their values to produce the value for middle pixel. It is computationally fast algorithm. Comparatively smaller no of pixels employed by bilinear interpolation will give more good results that is pleasing to eye with fewer artifacts. In FCBI method if the local image variation is not too big, roughly approximating the curvature for the profile describing the brightness of the image along the selected direction. So by focusing on these two interpolation methods it has been proposed a new algorithm here.

Hybrid Super resolution Algorithm:
Step 1: Make the double size of image grid for the original image.
Step 2: Find features (eg: edges) in the original image
Step 3: At feature points, interpolate the image by FCBI method
Step 4: At non feature points, use a weighted averaging of the neighbors.
Step 5: Finally bilinear interpolation is performed for pixels at non feature points.

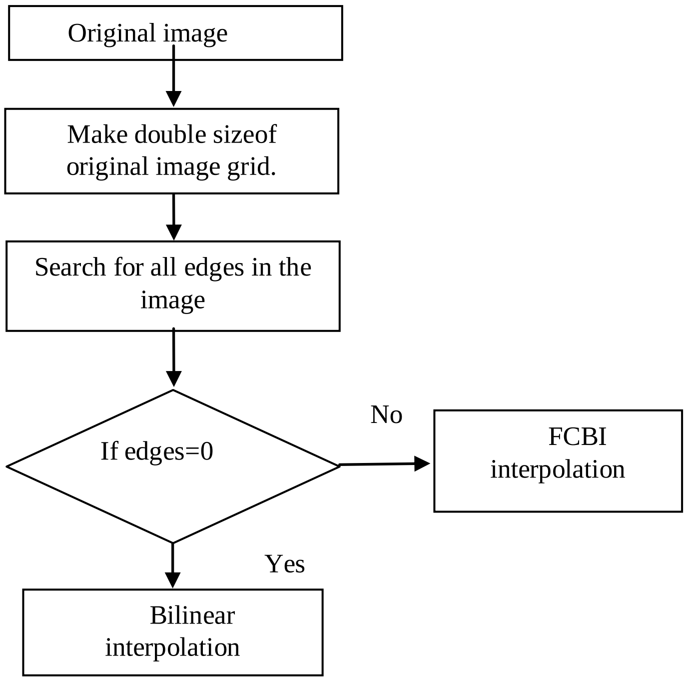


Fig 2: proposed method diagram

Feature Extraction:
Sometimes the features in the image are blurry or distorted**.** By enhancing these features only the resolution of the image can be increased. The features used for improving resolution can be edges, texture, and color. Using optimization and other techniques the geometrical features in the image can be improved which will give you good result in the resolution.

Edge detection:
Edges in an image may contain important content of an image. So in order to get any structural information strong edge detection is needed always. Here canny edge detection has been used. The first criteria for canny edge detection are low error rate that is edges should be identified accurately. The second criteria are the edge points should be well localized. A third criterion is only one response to a single edge.

Bilinear interpolation:
It is a linear type interpolation. Bilinear interpolation builds and evaluates two linear

interpolation functions for both horizontal and vertical direction. It interpolates between four nearest mapped neighbors. Here new fractional part of address is calculated using small neighborhood of pixel brightness. This will reduce the visual distortion produced by the fractional zoom. We have to calculate four interpolation functions for grid point. The linear interpolation kernel for that is given by

U(x) = { 0 |x|>1

{1-|x| |x|<1

Where x = distance between interpolated point and grid point.

Suppose our image is 3x3. We made double the size of grid and copied values to it.

A11	A12	A13
B21	B22	B23
C31	C32	C33

Fig 3: Original Image

A11	X	A12	x	A13	
X	*	x	*	x	
B21	X	B22	x	B23	
X	*	x	*	x	
C31	X	C32	x	C33	

Fig 4: New image (I)

Now we have to calculate values for new pixels. For that first we do row wise interpolation.

It starts from I(0,1) to I(i-1,j-1)

For i is even and j is odd we do I(2i,2j)=((2i,2j-1)+(2i,2j+1))/2

Now we interpolate column wise that is from I(1,0) to I(2i-1,2j-1)

For I is odd and j is odd we do I(2i,2j)=((2i-1,2j)+(2i+1,2j))/2

In the second iteration that starts after all row wise and column wise filling from I(1,1)to I(2i-1,2j-1)

For I is odd and j is odd we do I(2i,2j)=((2i+1,2j)+(2i-1,2j)+(2i,2j+1)+(2i,2j-1))/4

The last row and column are deleted due to row and column redundancy.

FCBI method:

In this method compute the second order derivative in two diagonal directions and interpolate the pixel with the lower derivative. The two diagonal direction are given by I_{11}(2i+1,2 j+1) and I_{22}(2i+1,2 j+1) using 12 neighborhood.

I_{11} (2i+1,2 j+1) = I(2i-2,2 j+2)+I(2i,2 j)+I(2i+2,2 j-2) -3I(2i,2 j+2)-3I(2i+2,2 j)+I(2i,2 j+4)+I(2i+2,2 j+2)+I(2i+4,2 j)

I_{22}(2i+1,2 j+1) = I(2i,2 j¡2)+I(2i+2,2 j)+I(2i+4,2 j+2)-3I(2i,2 j)-3I(2i+2,2 j+2)+I(2i,2;2 j)+I(2i,2 j+2)+I(2i+2,2 j+4)

The interpolated values at (2i+1,2j+1) is become

(I(2i,2 j)+I(2i+2,2 j+2))/2 if I_{11}(2i+1,2 j+1) > I_{22}(2i+1,2 j+1), (I(2i+2,2 j)+I(2i,2 j+2))/2 otherwise

Where I(2i,2j) is the enlarge image approximated by a factor of 2 by copying original pixels (indexed by i, j) into an enlarged grid.

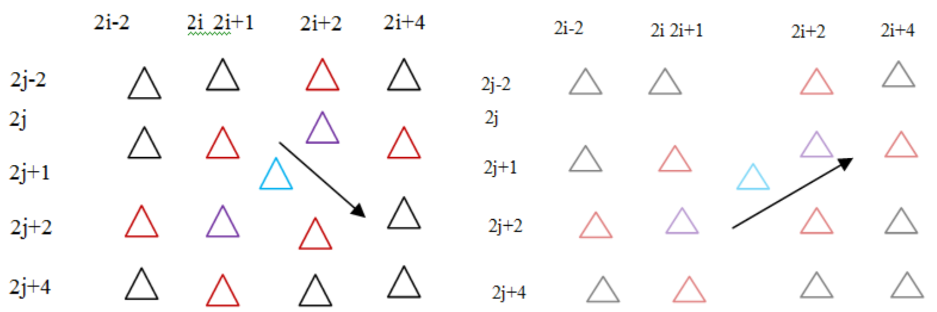


Fig 5: At each time FCBI algorithm fills the Central pixel (blue) with the average of the two neighbors in the direction of the lowest second-order derivative (I_{11}or I_{22}). I_{11}(left side) and I_{22}(right side)are estimated using for each one the eight-valued neighboring pixels which is shown in different colors.

3.2 Features of proposed algorithm

- We have used a combination of linear interpolation algorithm and adaptive interpolation algorithm with an edge detecting criteria. Based on edge feature we interpolate the image.
- Edges are strong features to identify any nodules, calcification or tumor in the mammogram. Here our aim is to increase natural texture and reduce the computation time.
- The advantage of bilinear technique is that it contains minimum quantifiable error. FCBI provides edge preserving sharp images comparing with the NEDI method.
- Pixilation, over smoothing, jagged artifacts is almost avoided in this method. The image is upscale adaptively using local second order information.

4 Results and Discussion

System Specifications:

MATLAB 2013a is used. The experiments were carried out in a system having Intel®

Core TM i3 processor with speed2.2 GHz and 3GB RAM.

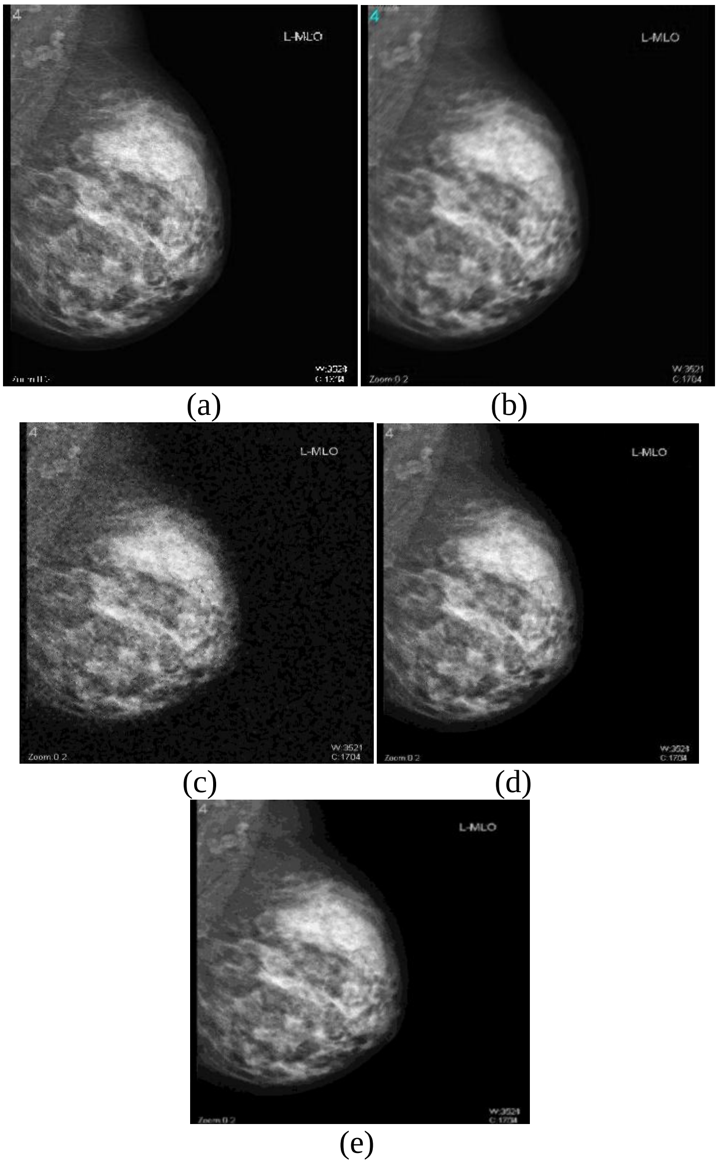
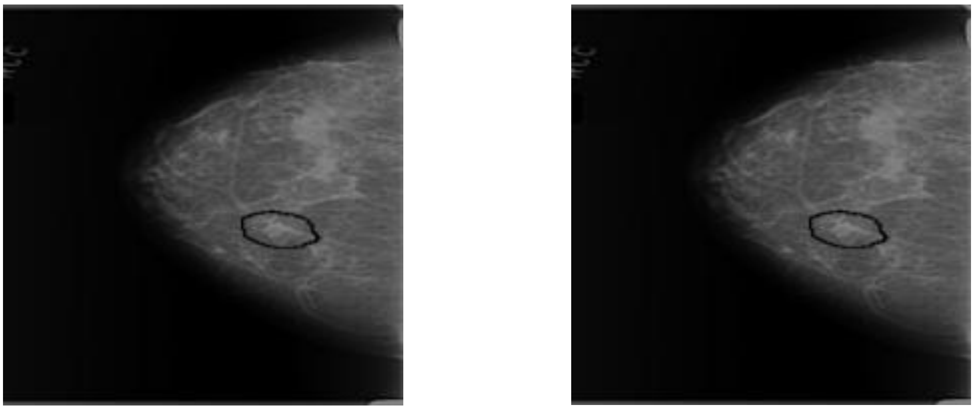


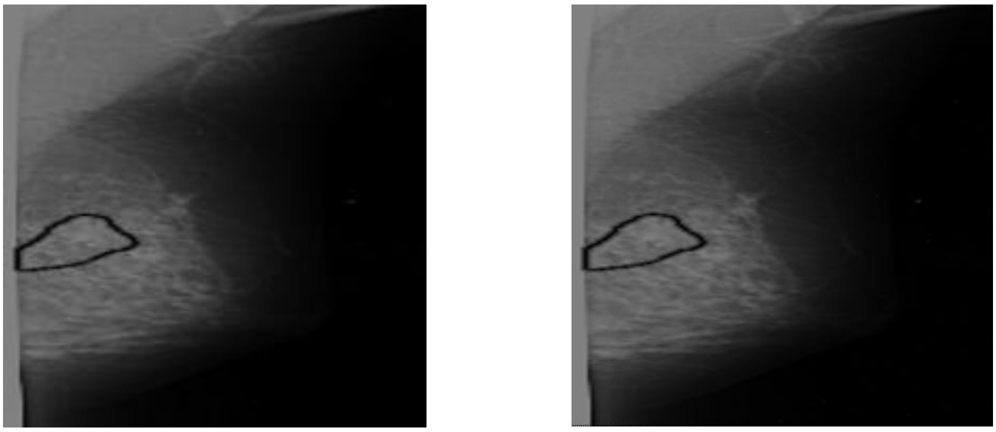
Fig 6: Different steps for super resolution a) registered image b)deblurred image c)denoisy image d)wavelet fused image e)proposed algorithm

Results for other type of mammograms also shown below,



(a) (b)

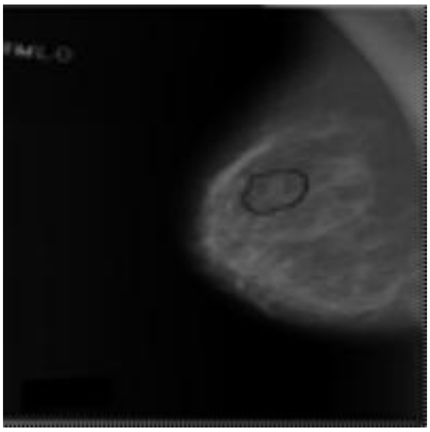
Fig 7: SR for begin mammogram (a) begin type mammogram (b) mammogram after using our proposed method



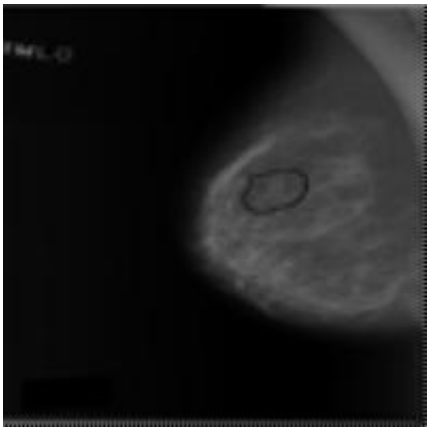
(a) (b)

Fig 8: SR for cancer mammogram. (a) Cancer type mammogram (b) mammogram after using our proposed method

The marked region in the begin and cancer type mammograms shows the tumor region. After using proposed algorithm the tumor region is enlarged and it is more visible. The size of tumor is different in begin and cancer type mammogram



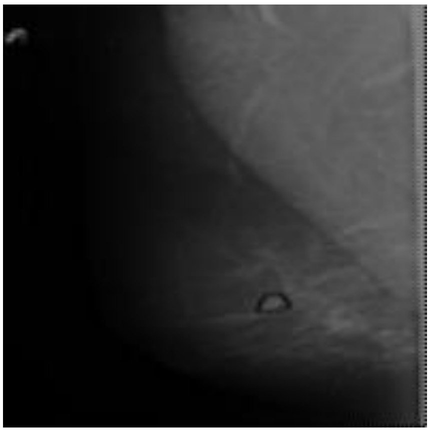
(a)



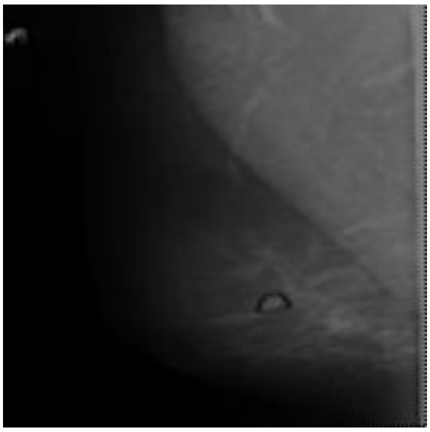
(b)

Fig 9: SR for begin1 mammogram which is having a calcification in the rounded region (a) Begin1 mammograms (b) begin 1 mammogram after using our proposed method.

In Fig 9 the calcification in the begin1 mammogram is being enlarged using proposed method and it is clearer.



(a)



(b)

Fig 10: SR for cancer 1 mammogram which is having a mass in the rounded region (a) cancer 1 mammogram (b)cancer 1 mammogram after using our proposed method

In Fig 10 the cancer 1 mammogram is having a mass in the rounded region it has been enlarged using proposed method and became more visible here.

Our algorithm works for other images also.

(a) (b)

Fig 11: monkey image (a) Original image (LR) (b) proposed method

4.1 **Quantitative analysis**:
The strength of our proposed algorithm has been checked using PSNR values. It is noted that by increasing the image size we get high PSNR values and less mean square error using our proposed algorithm. It is shown in table 1. The tested mammograms contain normal, begin and cancer type mammograms. From the table it may be seen that for resolution 100x100,200x200 and 300x300 the different type of mammogram having higher PSNR value at 300x300 resolution.

Table 1: PSNR values of increasing the image resolution

Image	Interpolation at 100x100	Interpolation at 200x200	Interpolation at 300x300
Mammogram	36.63	37.78	37.37
Begin	33.69	37.12	39.15
Begin1	33.64	34.69	36.92
Cancer	40.30	43.42	45.32
Cancer1	34.87	38.22	39.82
Normal1	33.55	31.31	31.46

Table 2: PSNR values of different methods

Image	Bilinear Interpolation	FCBI Interpolation	Proposed Interpolation
mammogram	36.15	36.19	36.63
Begin	33.69	33.40	33.64
Begin1	33.64	33.46	33.60
Cancer	40.61	38.90	40.30
Cancer1	34.87	34.64	34.93
Normal1	33.89	32.43	33.55

In Table 2 it is shown that we have done three interpolation techniques individually. Comparing with bilinear interpolation and FCBI method our proposed algorithm gives the best result for PSNR values. Here our data set has been tested individually for bilinear interpolation, FCBI method and our proposed method. Comparing with the FCBI method mammograms have good PSNR values for bilinear interpolation. But our proposed algorithm gives better result than bilinear interpolation for cancer type mammograms. For other types also it is equally good. So by increasing the quality of resolution the analyst can easily detect the masses and micro calcification in the mammogram. Here with less radiation we are getting a high resolution image.

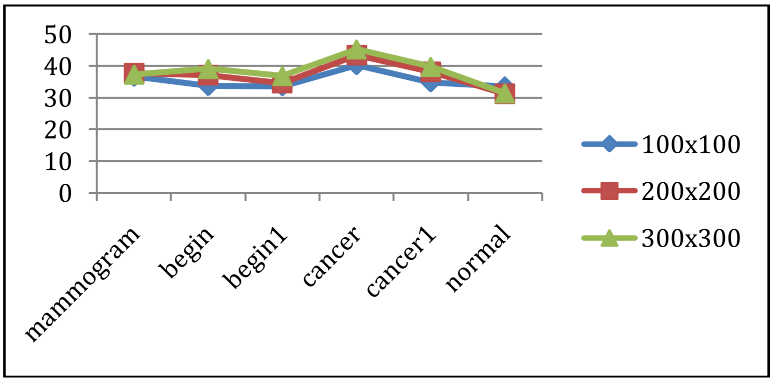


Fig 12: Showing the graph of PSNR values for increasing resolution

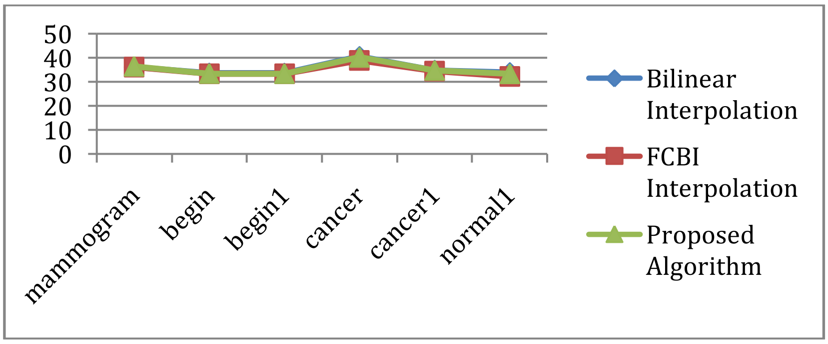


Fig 13: showing the graph of PSNR values for different interpolation method

Mean Square Error(MSE):

Usually there are two performance index metrics are used to get the image compression rate that are object fidelity and subject fidelity criteria. It is very important to calculate the energy loss in the lossy energy compression. Say our original image is *f*, the two image get same type of degradation the one with lower MSE value will be more close to the original image. The degradation type also depends in the MSE values. The mean square error between original image *f*(m,n) and the reconstructed image *g*(m,n) with MXN pixels are given by

$$MSE=\frac{1}{MxN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(f(\mathrm{m,n})-g(\mathrm{m,n}))^{\wedge}2.$$

Peak Signal To Noise Ratio (PSNR):

Peak to signal ratio is the objective quality measurement used for distortion. PSNR is a constant noise measure. For comparing with the different coding algorithms PSNR values are very useful and give you best quantitative measure.

$$PSNR= 10 * \log_{10}[\frac{(255)^{\wedge}2}{MSE}]$$

5 Conclusion

It has been implemented a super resolution algorithm for mammograms here. The various type mammogram like normal, begin and cancer having its low resolution data sets. The low resolution mammograms have been processed with registration, denoising and deblurring techniques. All the processed images is then fused to get a single image from low resolution dataset. Then we apply our proposed algorithm to increase resolution of the image. It is the combination of bilinear interpolation and FCBI method with an edge detecting criteria. The proposed method is giving us good PSNR results. Further to increase PSNR values we can make improvements on FCBI method. By increasing the weight and using optimization technique the PSNR values can be improved. Also by considering other features that is apart from edges the algorithm can be modified and hence PSNR values can also be improved.

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