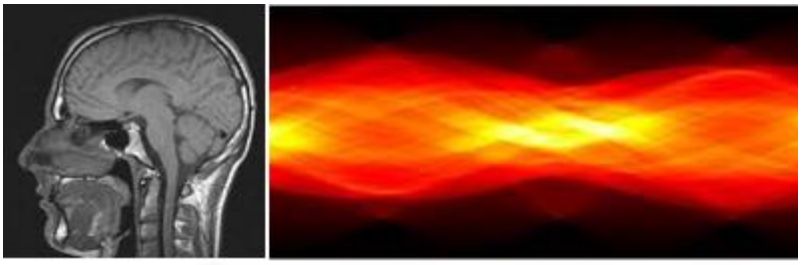

2020

A MONOGRAPH ON MRI IMAGES RECONSTRUCTION USING GENERATIVE ADVERSARIAL NETWORK

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Preface

This monograph introduces a Magnetic Resonance Imaging (MRI) reconstruction, which gives rapid achievement and it is more advantageous for many clinical application. Functional brain imaging in humans as we presently know it began when the experimental strategies of cognitive psychology were combined with modern brain imaging techniques, first positron emission tomography (PET) and then functional magnetic resonance imaging (fMRI), to examine how brain function supports mental activities. This marriage of disciplines and techniques galvanized the field of cognitive neuroscience, which has rapidly expanded to include a broad range of the social sciences as well as basic scientists interested in the neurophysiology, cell biology and genetics of the imaging signals. While much of this work has transpired over the past couple of decades, its roots can be traced back more than a century.

In 1927 Egas Moniz, professor of neurology in Lisbon and Nobel Prize in Physiology or Medicine winner in 1949, introduced cerebral angiography, whereby both normal and abnormal blood vessels in and around the brain could be visualized with great accuracy. In its early days this technique likewise carried both immediate and long-term risks, many of them referable to deleterious effects of the positive-contrast substances that were used for injection into the circulation. Techniques have become very refined in the past few decades, with one in 200 patients or less experiencing ischemic sequelae from the procedure. As a result, cerebral angiography remains an essential part of the neurosurgeon's diagnostic imaging armamentarium and, increasingly, of the therapeutic armamentarium as well, in the neurointerventional management of cerebral aneurysms and other blood-vessel lesions and in some varieties of brain tumor.

This monograph introduces a Magnetic Resonance Imaging (MRI) reconstruction, which gives rapid achievement and it is more advantageous for many clinical application. This reduces the scanning cost as well as image reconstructed in very less time, this will be advantage for real time technology. This paper confer a deep learning based plan for reconstruction of MRI images. In our Generative Adversarial Network (GAN) designed a generator which gives the better enhancement like texture smoothness, and high resolution to MRI images, Also find the ` In addition including the frequency domain information to embed similarity in both the images using parameter Structural Similarity Index (SSIM). Also performed radon transform to find the structural similarity of images with enhancement, accuracy and test whether the images are real or fake. Compared to other method, our GAN method provides superior reconstruction.

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Magnetic Resonance Imaging (MRI) is mostly used for scanned imaging application. MRI scans the body tissue and gives excellent contrast, which also includes the structural and functional information of whole body. The main drawback of MRI is slightly slow speed because data samples cannot directly collected in image, but rather than in specific area. This data has special time period information, it collects data serially. For high quality of image upto 512 lines of data needs. During MRI patients movement and other physiological motion gives slow speed. MRI data samples are obtain sequentially in k-space. K-space determined by Nyquist-Shannon sampling criteria. Under-sampled k-spaces, gives the result; acceleration rate is directly proportional to the under sampling ratio. In that principle only less amount of data required.

I would like to acknowledge the contribution of **Priyanka Milind Shende,** M.Tech student .I personally thank our Head of Department **Dr.P.T.Karule** who has given full support for completing this work. I also acknowledge the support provided by my Co-author **Dr. N.P. Patidar** for his contribution in this monograph. Last but not the least I thank my wife **Mrs.Pushpalata Pawar** for her support.

Prof. Mahesh S. Pawar

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List of Abbreviations:

The abbreviations used in this report are listed below

GAN	Generative Adversarial Network
MRI	Magnetic Resonance Imaging
CS	Compressed Sensing
PG	Perceptual GAN
PPG	Pixel Perceptual GAN
PPGR	Pixel Perceptual GAN Refinement
PFPGR	Pixel Frequency Perceptual GAN Refinement
SSIM	Structural Similarity Index
PSNR	Peak Signal to Noise Ratio
MSE	Mean Square Error
CNN	Convolutional Neural Network
CT	Computed Tomography
SMASH	Simultaneous Acquisition of Spherical Haemonics
NMR	Nuclear Magnetic Resonance

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ABSTRACT

This paper introduces a Magnetic Resonance Imaging (MRI) reconstruction, which gives rapid achievement and it is more advantageous for many clinical application. This reduces the scanning cost as well as image reconstructed in very less time, this will be advantage for real time technology. This paper confer a deep learning based plan for reconstruction of MRI images. In our Generative Adversarial Network (GAN) designed a generator which gives the better enhancement like texture smoothness, and high resolution to MRI images, Also find the ` In addition including the frequency domain information to embed similarity in both the images using parameter Structural Similarity Index (SSIM). Also performed radon transform to find the structural similarity of images with enhancement, accuracy and test whether the images are real or fake. Compared to other method, our GAN method provides superior reconstruction.

A group of two images gives a reconstructed image using radon transform. Once the reconstruction is done, after applying radon transform on reconstructed images get the image same as it is.

Keywords—Magnetic Resonance Imaging (MRI); Fast MRI; Deep learning; Generative Adversarial Network(GAN), Generator, Discriminator.

INTRODUCTION

Magnetic Resonance Imaging (MRI) is mostly used for scanned imaging application. MRI scans the body tissue and gives excellent contrast, which also includes the structural and functional

information of whole body. The main drawback of MRI is slightly slow speed because data samples cannot directly collected in image, but rather than in specific area. This data has special time period information, it collects data serially. For high quality of image upto 512 lines of data needs. During MRI patients movement and other physiological motion gives slow speed. MRI data samples are obtain sequentially in k-space. K-space determined by Nyquist-Shannon sampling criteria. Under-sampled k-spaces, gives the result; acceleration rate is directly proportional to the undersampling ratio. In that principle only less amount of data required.

The main challenge face CS-MRI is to find method that can reconstruct uncorrupted or de-alised scanning image from highly undersampled k-space data. The application of MRI provides a key motivation for compressive sensing (CS).The scanning data depends on type of scanning appliances. Projection data is getting from the computed tomography scan devices and K-space data getting from the MRI images. Previous technology take lot of scanning time to produce detecting quality images, but in our experiment scan time reduces without sacrificing the imaging quality. We introduced a new conditional generative adversarial network based fast CS-MRI by vast extension of our preparatory proof-of-concept study and deep learning architecture for de-aliasing. We propose GAN architecture for generator network with skip connection, for fast convergence we designed a constant purified training approach of GAN. The adversarial loss is combining with new content loss considering both pixel-wise mean square errors (MSE); pretrained deep convolutional network defines perceptual loss.

On the other side, Compressed sensing based MRI gives fast acquisition which depends on Nyquist-Shannon sampling criteria. It gains the reconstruction without affecting image quality with the help of non linear optimization.

1.1 Problem Statement

Nowadays many researchers focuses on generative Adversarial Network. So that patient comfortable with imaging. There is a lot many methods for reconstruction of MR images but after analysation the generative adversarial network provides better reconstruction and faster also than other method.

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The main problem focus in this thesis is the reconstruction of images so that if again reconstruct the already reconstructed image it gives as it is. There is no other method or any parameter except GAN to reconstruct again to get better image because it gives the accurate enhancement.

As mentioned in the initial problem statement, the basis for the project is to see if a computer vision system can be developed, that allows a robot to understand their environment. One way to accomplish this, could be generative models, which learns about our world, by generating data like it. Based on the initial problem statement and preliminary analysis, the final problem statement is expressed as: Can a system be developed, which unsupervised can learn to perform semantic segmentation, by encouraging it to generate similar data.

1.2 Objective of the thesis work

Based on the previous discussion, the main objectives in the presented GAN designs are:

- Present new mathematical models for the GAN algorithm which provides faster reconstruction.
- Increasing the speed of reconstruction and reduces the noise presented in images.
- Provide better preserve texture and edges in the reconstruction.
- Provides superior reconstruction with preserved perceptual image detail.
- Provide an accurate structural visualisation of images.
- The development and characterization of MRI through radon transform.

1.3 Contribution and Organization of Thesis

Main contributions of this thesis are:

- Mathematical Analysis of GAN and inverse radon transform algorithm.
- Study of different types of GAN algorithm.
- Design of GAN algorithm for faster reconstruction.

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- Implement radon transform to combine two images.
- Analysis of structural similarity of images through radon transform and generative adversarial network.

The thesis report is organized into six chapters. The chapter wise detail is given below:

Chapter 1: In this chapter, the objective of the thesis work is presented.

Chapter 2: This chapter is based on Literature review, overview of Generative adversarial Network and radon transform

Chapter 3: In this chapter, brief introduction about the project work is presented with GAN implementation.

Chapter 4: This chapter deals with the implementation results of each block of proposed method.

Chapter 5: Under this chapter Summary, Conclusion and Future Scope of this algorithm is discussed

Chapter 6: This chapter presents the cited reference.

1.4 Operating System and Software used

The operating system and Software used in thesis are as follows:

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Operating System: Windows 7, Windows 8, Windows 10.
Software Used: Matlab R2016b.

2.1 Literature Review:

M. Mardani, E. Gong, J. Y. Cheng, S. Vasanawala "Deep Generative Adversarial Networks for Compressed Sensing Automates MRI", proposed an novel compressed sensing framework for faster and more valuable image reconstruction from undersampled data. Reconstruction made on historical data for higher resolution sharp and effective contrast. Uses a LSGAN for training generator which contains the undersampled images for reducing aliasing artefacts.[1]

O. Oktay, W. Bai, M. Lee, R. Guerrero, K. Kamnitsas "Multi-input cardiac image super-resolution using convolutional neural networks", present paper on Multi-input cardiac image super resolution using Convolutional Neural Network. Multiple data takes from different plane for improved performance cardiac short and long axis magnetic resonance images gives output as CNN approach well performed state-of-art super resolution (SR) method. Also perform segmentation and motion tracking benefits.[2]

C. H. Pham, A. Ducournau, R. Fablet, and F. Rousseau "Brain mri super-resolution using deep 3dconvolutional networks", presents SRGAN, a generative adversarial network for image super resolution. Develop a framework for photo realistic neural image for 4× upscaling factor. To achieve this uses a perceptual loss and content loss presented in adversarial loss. This is the best solution to train the image using discriminator network and differentiate between super resolved images and original photo-realistics images.[3]

C. Ledig, L. Theis, F. Huszar, J. Caballero, "Photo-realistic single image super-resolution using a generative adversarial network", proposed a deep Three Dimensional (3D) convolutional neural network (CNN) for super resolution of brain images . Extend super resolution images to multimodal super resolution using intermodality.[4]

Y. Jia, A. Gholipour, Z. He, S. K. Warfield "A new sparse representation framework for reconstruction of an isotropic high spatial resolution mr volume from orthogonal anisotropic resolution scans", proposed a algorithm multiframe super-resolution (SR) reconstruction based on sparse representation of medical MR images corresponding data between high resolution (HR) slices and low resolution (LR) section scans also find the self similarity between then to upsample the input scan. The upsampled input images are correlate using wavelet fusion merge and error backprojection to reconstruct an image achieves good peak signal to noise ratio (PSNR), structural similarity index (SSIM) and intensity.[5]

Du, C., Du, C., and He, "Sharing deep generative representation for perceived image reconstruction from human brain activity", worked on reconstruction of visual stimulus of missing view in different view variable structure shares a common latent representation using generative adversarial network extracts the nonlinear features from visual data and correlation between voxel activities of FMRI recordings . This activities are very tough for removing noise and improving prediction. 3 FMRI recording are more precisely reconstruct.[6]

K. G. Hollingsworth, "Reducing acquisition time in clinical MRI by data undersampling and compressed sensing reconstruction," presents a tentative GAN based profound learning technique for quick CS-MRI recreation. The profound de-associating generative ill-disposed system strategy perform superior customary CS-MRI technique and furthermore increase comaparable remaking contrasted with recently created strategies, however handling time has been surprisingly decreased and empowers conceivable constant has been amazingly diminished and empowers conceivable continuous application. By converging with existing MRI checking successions and parallel imaging, we can anticipate this reenactment based investigation to be meant the genuine clinical condition.[7]

M. Lustig, D. L. Donoho, J. M. Santos, and J. M. Pauly, "Compressed sensing MRI", Exhibition utilizing WGAN enhances picture quality and scientific properties. When we looking at the pictures quality and investigative properties. While looking at the CNN and WGAN pictures, WGAN system help to avoid smoothing impact. Regardless of whether CNN and WGAN noticeably share a comparative outcome the quantitative pursuit indicates WGAN

appreciates more prominent PSNRs and increasingly honest scientific properties of denoised pictures close to NDCT pictures. Spoken to learning based system to get veils for compressive MRI utilizing preparing signs to make ideal for a given decoder and body structure. [3] As well as having a precise legitimization through measurable learning hypothesis our methodology apparently provides improved execution on true informational collection for a different recreation strategies. After the entirety of our structure is most appropriate to general translates, it can presumably be utilized to upgrade the records for new reproduction strategies that prior to be found. In this work we focus on 1D subsampling for 2D MRI and 3D MRI, 2D subsampling for 2D MRI and non Cartesian examining.[8]

S. Ravishankar and Y. Bresler, "MR image reconstruction from highly undersampled k-space data by dictionary learning", Compressed detecting based attractive resonance imaging has been centered around three noteworthy bearing. In first research finds the amazing undersampling method, which make ludicrous undersampling artefacts. With the assistance of muddled undersampling artefacts we can apply appropriate nonlinear recreation to commotion – like ancient rarities without influencing nature of picture in the reconstruction. Most imperative the arbitrary undersampling plan must be effectively actualized on MRI scanner and reasonable with specific checking successions. Second Medical symbolism acquire by MRI is normally compressible. CS-MRI utilizes the certain sparcity to recreate quickened securing. Framework of picture pixels or crude information focuses having zero esteem or compressible is called sparsity. Such sparness may show either in theimage or in change area.[9]

O. Michailovich, Y. Rathi and S. Dolui, "Spatially Regularized Compressed Sensing for High Angular Resolution Di usion Imaging", Another profound learning system presented for 3D tomographic reconstruction. We propose separated back-projetion-type calculation to neural system. After all the back projection can't be actualized as a completely associated layer because of its memory prerequisite. To take care of this issue we executed a cone bar back-projection layer. Which ascertain the forward pass. We likewise determine in reverse pass a projection task. Our new layer licenses joint enhancement of amendment ventures in volume and projection area. Profound convolution neural system (CNN) for low-portion X-beam CT and won the second place in 2016 AAPM low-portion CT incredible test. After all a portion of the surface were not

completely recouped. The new calculation were roused by late examination of the profound convolutional neural system (CNN) as torrential slide convolution framelet flag portrayal. Broad exploratory outcome affirm that the proposed system have enhance execution and detail surface of picture. A CS target work that limits cross-direct joint sparsity in the wavelet area .Our recreation condense this goal through iterative delicate thresholding, and accomodate normally with iterative self-steady parallel imaging (SPIRIT). In the same way as other iterative attractive resonanace imaging reproduction, l1-SPIRIT's picture quality comes at a high computational expense[10].

OVERVIEW OF GENERATIVE ADVERSARIAL NETWORK ALGORITHM

2.2 Notation and Conventions:

2.2.1 Magnetic Resonance Imaging

As magnetic resonance imaging is known to be the main diagnostic imaging tool for various disease, it is usually finite by the long adspection times. The prime factor for this is that for

encoding only a limited no. of information can be encoded only for one MR signal (FID or echo) and the counting has to be repeated lot many times. One of the major source of research is that increasing imaging speed. The first experiment was done in 1970s. And the result is improve which is advantageous for many clinical application. There is a one way to accumulate data acquired. Which reduces the no. of data points which are used to reconstruct an image with known resolution. At all the time this ignores the Nyquist-Shannon sampling theorem. The earlier fact is also reflect in this section. Which we have remove. This can be done by presence of extra a-priori knowledge during image reconstruction process. Example are using multiple channels for parallel imaging.

2.2.2 Definition and Brief of Generative Adversarial Network

A Generative Adversarial Network is a category of machine learning method. Two neural joint together in one frame . This scheme can generate photographs , video of GAN which at least gives the deep information to human sight seer. A generator generates the images on the other hand discriminator finds them. Typically generator generates the images from the latent space while the discriminator network tells the images produced by generator from the true data. The aim of GAN is to increase the error rate of discriminative network. “fool” the discriminator network by producing novel candidates that the discriminator thinks are not synthesized. Known dataset works as a starting data for discriminator, when taking the samples from training data it gives acceptable accuracy takes input images from latent space after that generated images are evaluate in discriminator. Backpropogation is applied on this images to get better images, generator is deconvolutional and discriminator is convolutional.

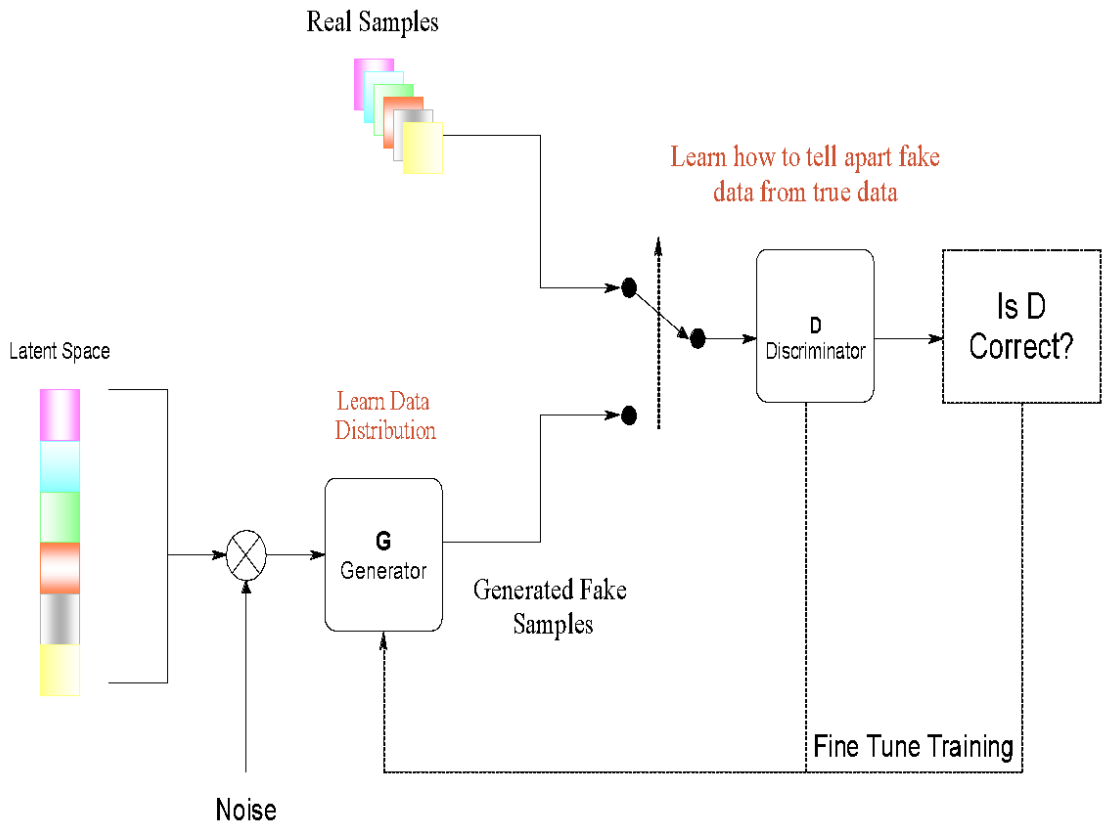


Figure 2.1 Block Diagram of Generative Adversarial Network

How does GAN work?

Generator

Input to the Generator is random noise created from the training data. Training data can be an image. Generator tries to mimic the input image as close as possible to the real image from the training data. Generator's goal is to fool the Discriminator.

Discriminator

Discriminator gets two inputs. One is the real data from training dataset and other is the fake data from the Generator. Goal of the Discriminator is to identify which input is real and which is fake.

Step 1: Train the Discriminator using the training data, x. Objective of Discriminator to maximize the probability of getting correct label. Output should be real for the training data and fake for data generated from the Generator.

Step 2: Take a random input from the training data and introduce noise to create random noise data z.

Step 3: Generator takes the random noise data z and tries to reconstruct the input x hat.

Step 4: Discriminator takes input from two sources. One input is the real input from the training data. Other input is the data generated by the Generator. Discriminator classifies input as real or fake. Based on classification, classification error is computed.

Step 5: We then back propagate the classification error to update the Discriminator. Objective of Discriminator is to minimize the classification error.

Step 6: Classification error is also back propagated to update the Generator. Objective of the Generator is to maximize the Discriminator classification error. Generator G generates a probability Pg as distribution of the samples G(z) obtained from z. To learn the generator's distribution Pg over data x, we define a prior on input noise variables Pz(z),D(x) represents the probability from the training data x rather than Pg GAN's need to optimize the minimax objective function. Minimax objective function Early in the training Discriminator will reject generated fake data from Generator with high confidence. Initially fake data would be different from the training data. As we train Discriminator to maximize the probability of assigning the correct labels to both training examples and samples from Generator. We simultaneously train Generator to minimize the Discriminator classification error for the generated fake data. Discriminator wants to maximize objective such that D(x) is close to 1 for real data and D(G(z)) is close to 0 for fake data. Generator wants to minimize objective such that D(G(z)) is close to 1 so that the discriminator is fooled into thinking generated G(z) is real. We stop the training when the fake data generated by the Generator is recognized as the real data.

2.2.3 Undersampling k-space

The first conception aback parallel imaging is that the fourier encoding can except replaced by spatial data contained in the received coil sensitivity. Therefore imaging acquired by undersampled data. Skips some costly encoding steps, which directly converts into saved measurement time. If every N^{th} is to be count th measurement is quick by component of N called as reduction or acceleration component. The content of 2D imaging, the undersampling is pasted in the phase encoding direction, on the other hand both phases encoding in 3D imaging. With th help of convolution theorem the convolution of each coil is being describe regular

undersampling is being well known with th help of multiplication with Dirac comb function in K-data.

2.2.4 Image Reconstruction

For finding input image ρ equation of signal is settle, to reconstruct the image from undersampled multichannel data. If we know about the profile of sensitivity of the latent space, so the signal equation represents a linear method. Which is solved numerically present method for solving the equation or elsewhere exploit the equation of image foe continuously sampling pattern like SENSE, or immaculate the inverse of sparse harmonic (SMASH) and it is profitable and done. To made large acceleration parallel imaging is used but for large acceleration it highly in bad condition so that is is not suitable for such factor. The effect of back propagation of the data of amplification of noise merges the data.

2.3 Radon Transform

We targeting to describe the radon transform of the image function and alterate the inverse of radon transform for reconstruction of image. Focuses only on 2D Radon Transform not withstanding any of the alterate could be easily generalized to 3D form.

The Radon transform (RT) of a distribution f(x,y) is given by

$$p(\xi,\varphi) = \int \quad f(x,y)\delta(xcos\varphi + ysin\varphi - \xi)dxdy$$

where δ is the Dirac delta function and the coordinates x, y, ξ , and φ are defined in the figure below.

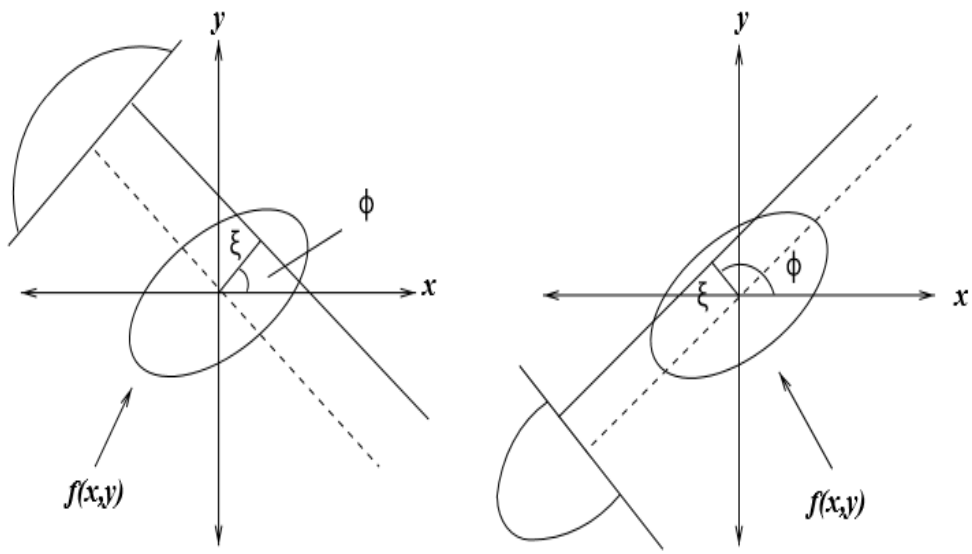


Figure 2.2 Coordinate system for the Radon transform.

The function p(ξ, φ) is often referred to as a sinogram because the Radon transform of an off-center point source is a sinusoid.The radon function computes projections of an image matrix along specified directions. A projection of a two-dimensional function f(x,y) is a set of line integrals. The radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction. The beams are spaced 1 pixel unit apart. To represent an image, the radon function takes multiple, parallel-beam projections of the image from different angles by rotating the source around the center of the image. The following figure shows a single projection at a specified rotation angle.

2.3.1 Parallel-Beam Projection at Rotation Angle Theta

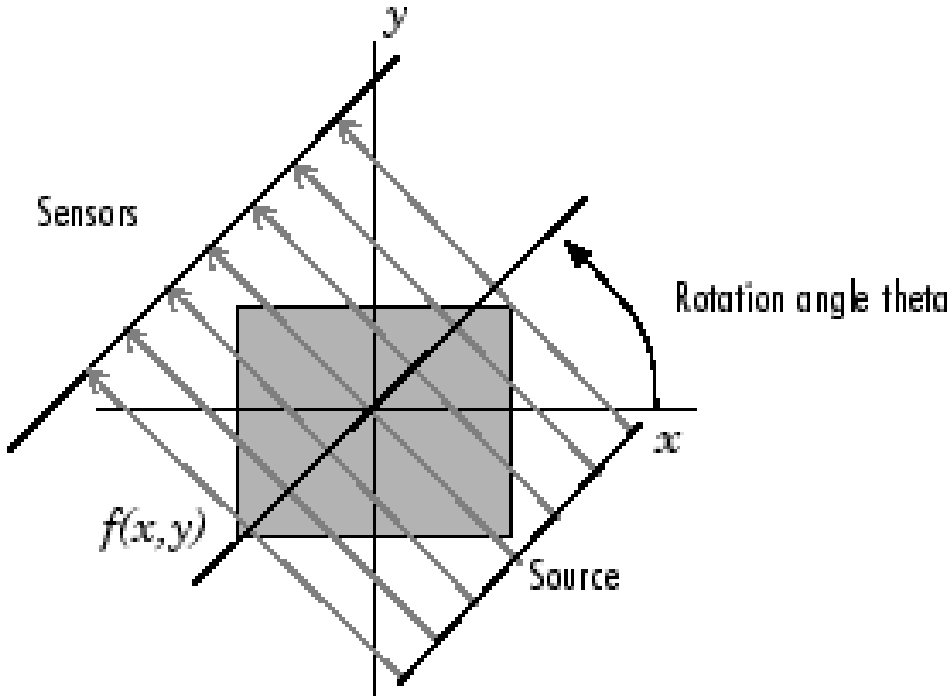


Figure 2.3 Radon Transform

For example, the line integral of f(x,y) in the vertical direction is the projection of f(x,y) onto the x-axis; the line integral in the horizontal direction is the projection of f(x,y) onto the y-axis. The following figure shows horizontal and vertical projections for a simple two-dimensional function.

2.3.2 Horizontal and Vertical Projections of a Simple Function

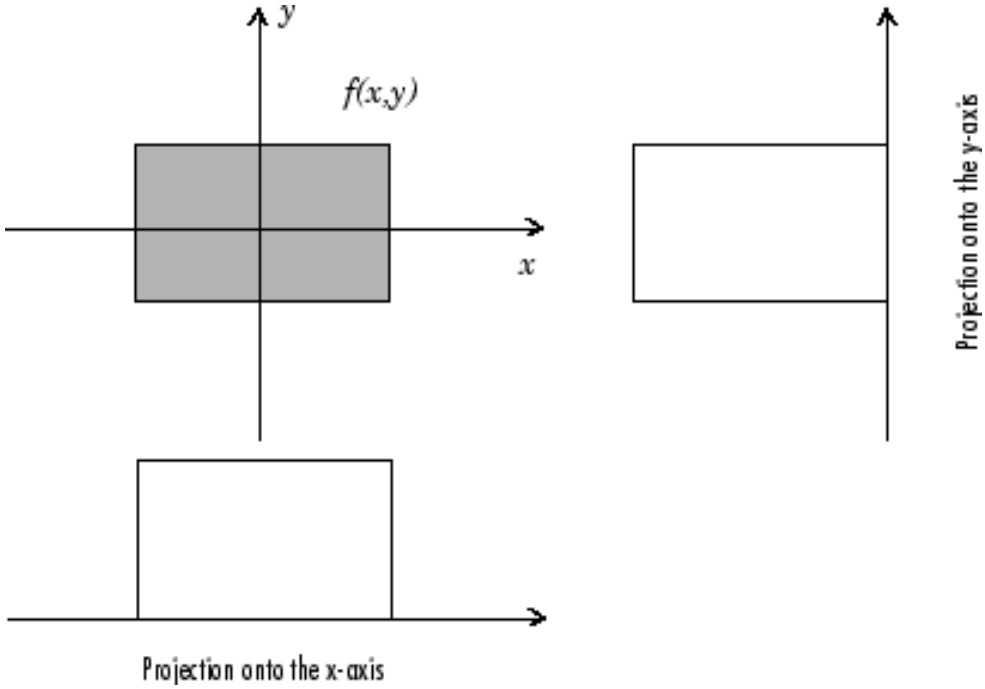


Figure 2.4 Horizontal and Vertical Projections of a Simple Function

Projections can be computed along any angle theta (θ). In general, the Radon transform of f(x,y) is the line integral of f parallel to the y axis.

2.3.3 Geometry of the Radon Transform

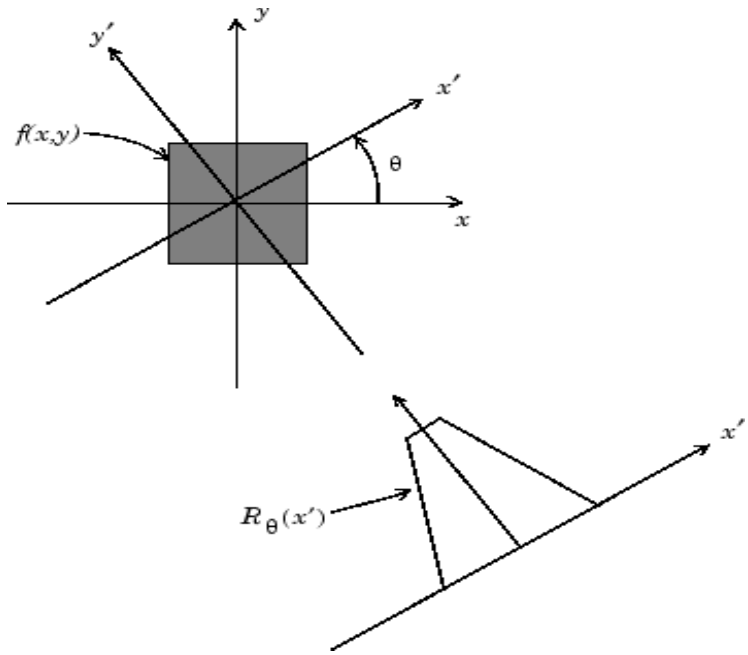


Figure 2.5 Geometry of the Radon Transform

2.3.4 Flow Chart of Radon Transform

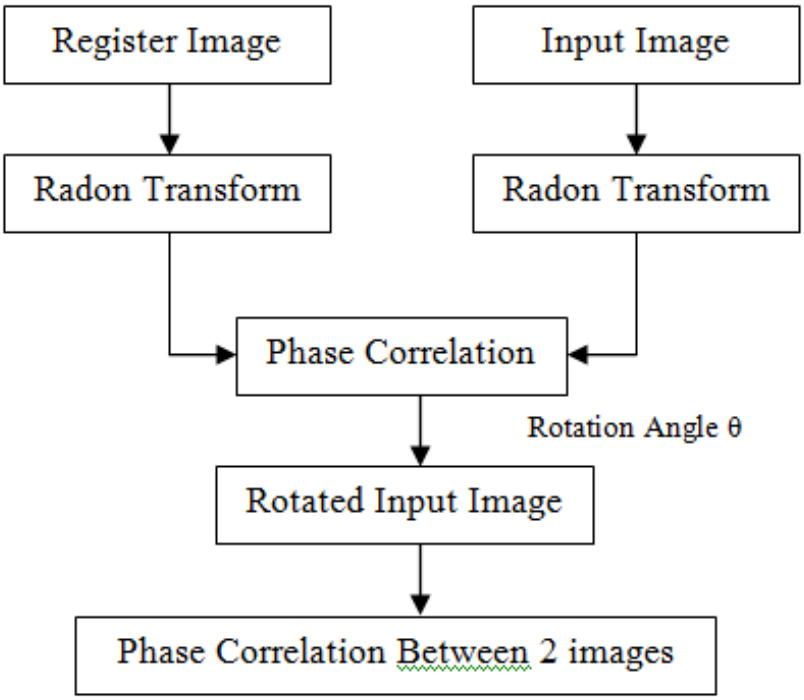


Figure 2.6 Flow Chart of Radon transform

The main point is to note that in these two images is that the four straight line of square shows the point of high intensity. The arrowed point shows the distance from the centre and orientation of lines. The intensity is very high means large value of R is obtain. The reason behind this is at a particular point X-ray passing straight according to the line are strongly absorbed at some instance one is miss it even this also heavily absorbed. Basically the overall nature of radon transform is to find the straight line in an image it is very advantageous for this work.

One another method for finding u(x,y) called filtered back projection algorithm. It work by assuming the original image is made up of the straight lines so it only enhance that straight lines to high value of R means to give high value. This method is very fast but not gives result accurately. u(x,y) is easy to find accurately and quickly but sometimes not gives proper result. The original development of such devices used a mathematical object known as Fourier transform to invert Radon transforms.

WORK DONE

3.1 IMPLEMENTATION OF GENERATOR

The generator – it seems like a decoder part in our GAN method takes the noise from the MRI images and try to convert this noise into the numbers. At the of this applying lot many iterative convolution. At first, I still not apply the batch normalization to generator so that it will not really not efficient so that going to apply batch normalisation layer on generator suddenly the learning of generator is getting changed. I have lot much big dense layer including generator input. The generator generates images which looks in output same as input it doesn't care about the what type of noise is present in the image eg. if the output is 9 that looked completely same. On the other side of if not used the dense layer at all operation on images in generator can't get any meaningful learning after lot many iteration for training the generator is seriously take quite efforts. Generative device understand the joint probability of p(x/y) from the output y reconstructs the input x, If the person has cancer in body in which location to find this features generator helps. It generates new data which includes all the features model from the sample data. Generative models helps reconstruct the input data. models learns the distribution of the individual classes Function well on outliers Generative modelling can generate new data points from the sample data.

3.2 IMPLEMENTATION OF DISCRIMINATOR

Now, we can define the discriminator. It looks similar to the encoder part. After generation of images as input, it takes real or fake numeric digits gray scale images on that gray scale image a no. of series of convolution are applied. After applying all the iteration use a sigmoid to sure about the images which are generated are real character. Discriminator devices learns the conditional probability p(y/x). This do without making any assumption about input distribution. This classifier learns evident the boundry between the data. Given data the model foreshow

which data belong to particular data. Given features like whether the person has cancer or not he smokes or not. Discriminative models do not perform well on outliers.

3.3 LOSS FUNCTION AND OPTIMIZERS

Now combine two parts each other like encoder and decoder so that we generate both discriminator object. The first one is acquire the real image and the second object receives the fake images, reuse the function and set second object True so that both object shares their variables we require both variable for finding two types of losses. The first loss is when receiving real images. The discriminator finds high value (close to 1) means received input images are real, while receiving fake images this finds low value (close to 0) means that the input images are not real it seem fake.

3.4 TRAINING GAN

After all, the interesting portion is begin, training GAN network! We serially transfers the images to generator which will help to find noise present in the object. We also concentrate on function that generator and discriminator are not strong while equilibrating losses otherwise this stops the network from learning anything or it will shows some disturbance while learning.

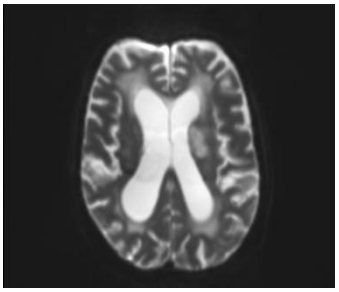
RESULTS AND DISCUSSIONS

A framework which depends on generative Adversarial network (GAN) for reconstruction and resolution. Generative adversarial network provide a very effective framework for generating MRI images with high perceptual quality. The GAN procedure promotes the reconstruction to

move closer to the search space with probability. In this paper describe the deep learning using GAN architecture to form a better reconstruction and high resolution.

4.1 Generative Enhancement

In the first step of generative enhancement collection of MRI images are stored into the database. For enhancement of scanned MRI image step wise generation are applied on image to get perceptual quality image. Performs smoothing to reduce noise, noise is anything in the image unwanted or unnecessary information. Using laplacian gaussian filter smoothing is perform to reduce noise in image. Due to presence of noise in image there is some improper data, with the help of supervised learning boosts the minor areas to get expected data, finally for intensity level clipping performed. After applying all parameters on image enhanced MRI image is reflected.



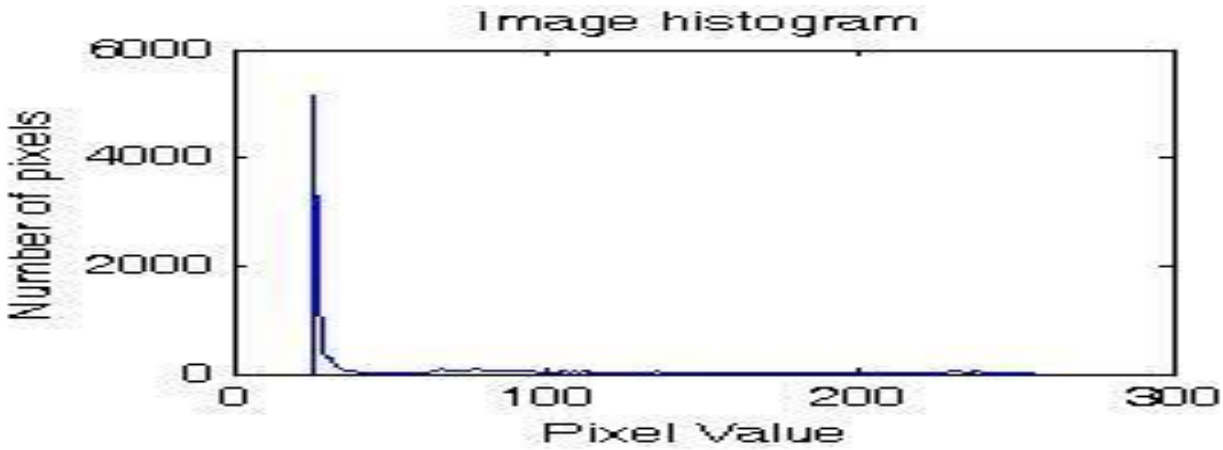


Figure 4.1 Histogram of input image

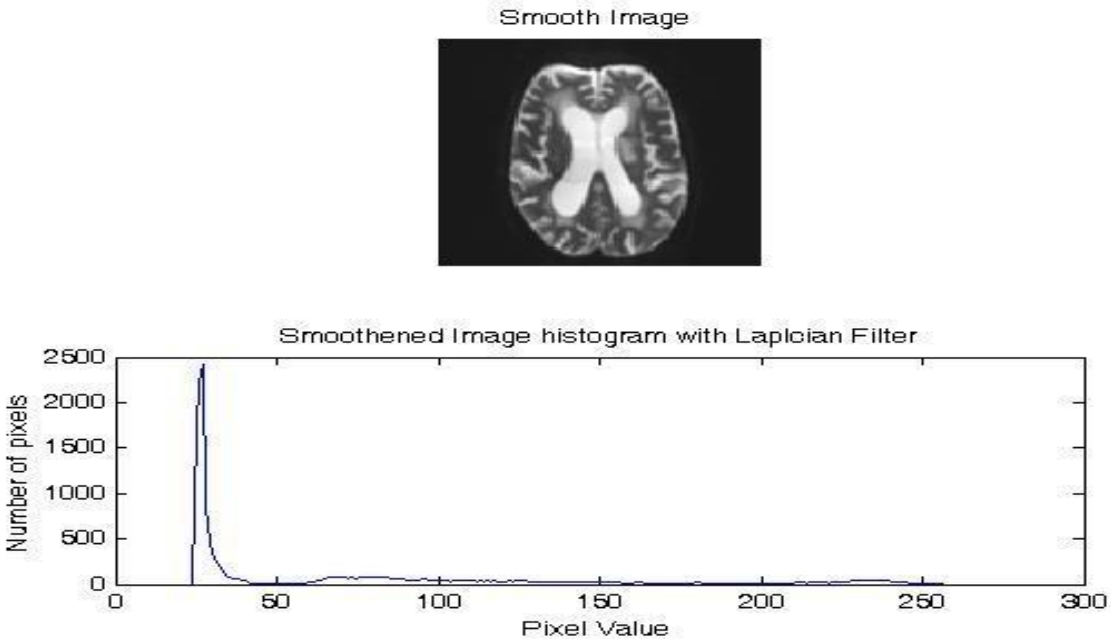


Figure 4.2 Smooth image histogram with laplacian filter

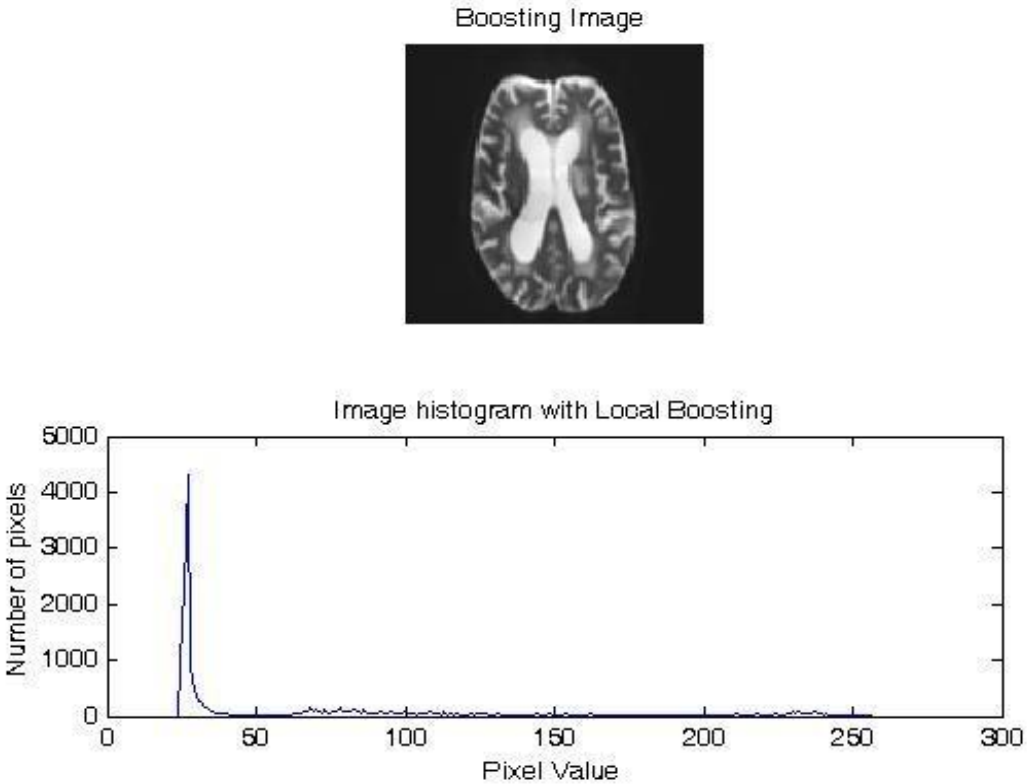


Figure 4.3 Image histogram with local boosting

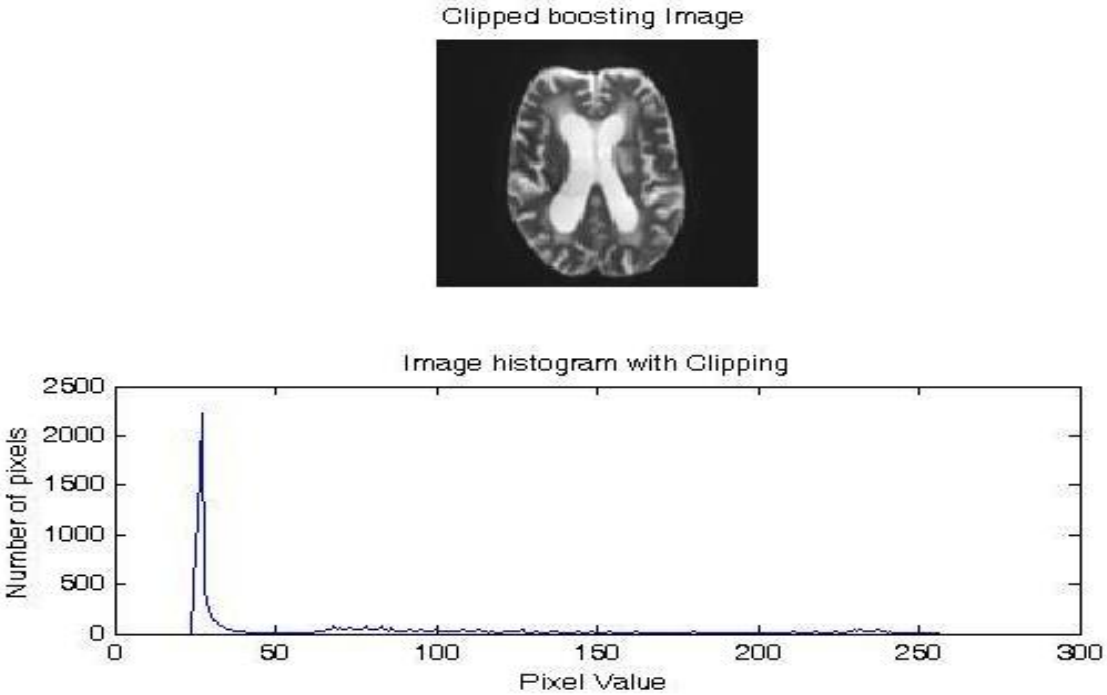


Figure 4.4 image histogram with clipping

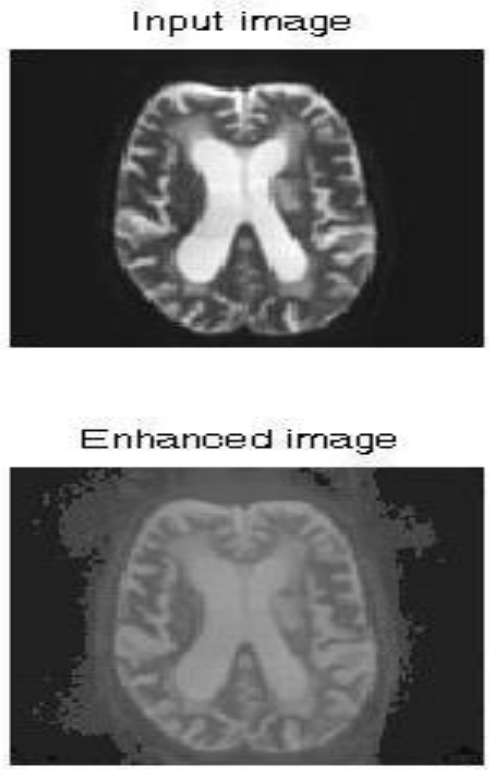


Figure 4.5 Generated Enhanced image

4.2 Image Segmentation

For image analysis and image understanding proper segmentation is necessary condition. Features such as color moments, texture or edge based methods are used for finding homogeneous regions in an image. Segmentation change the representation of an image that is more meaningful, classifies the pixels into object or group and easy to analyze. In this paper measurement is taken in K-space i.e., the value of k-space is 3 (K=3), k-space has spatial frequency information it collects data line by line.

K-space differentiated into three regions:

- White Region
- Gray Region
- Fluid Region

Double thresholding algorithm is used for removing unnecessary detail and bring out hidden details. Enhanced image is group of shape, texture and other information. Separated the white, gray and fluid region for analysis of further process to get an better image.

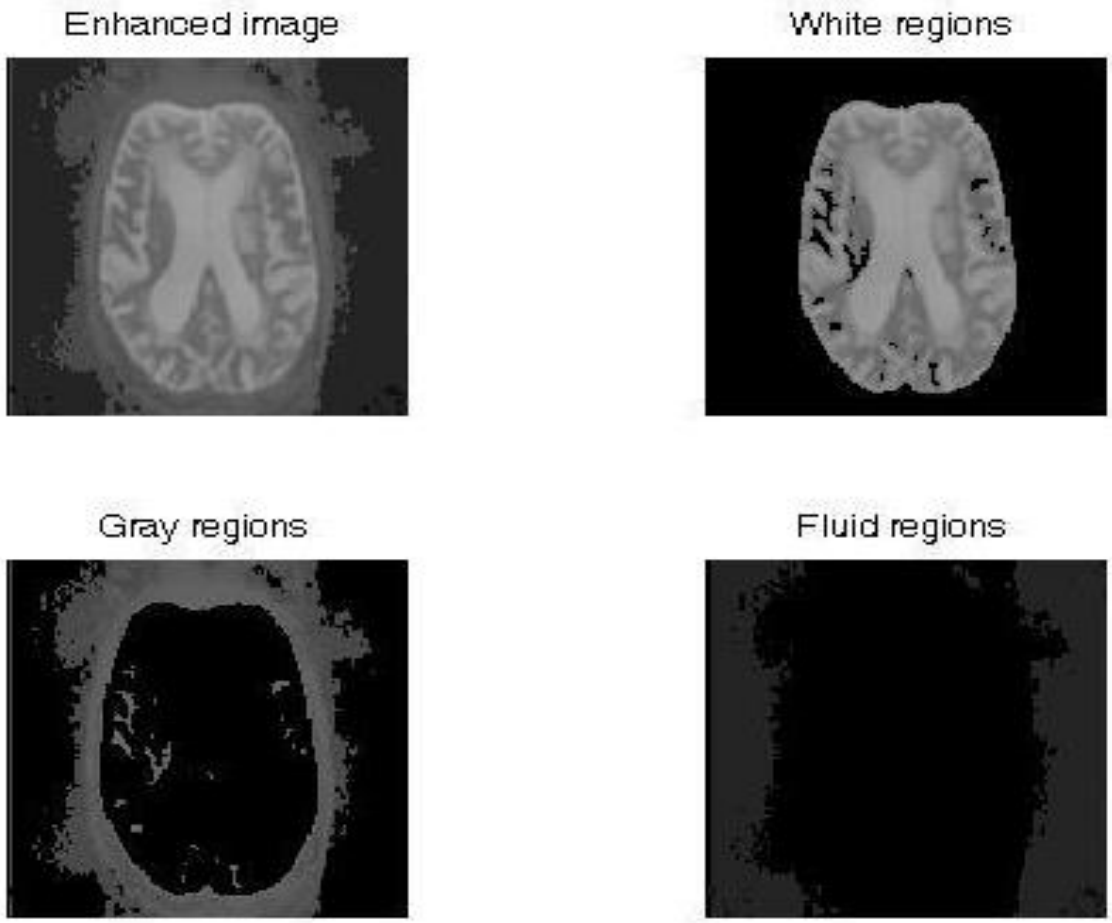
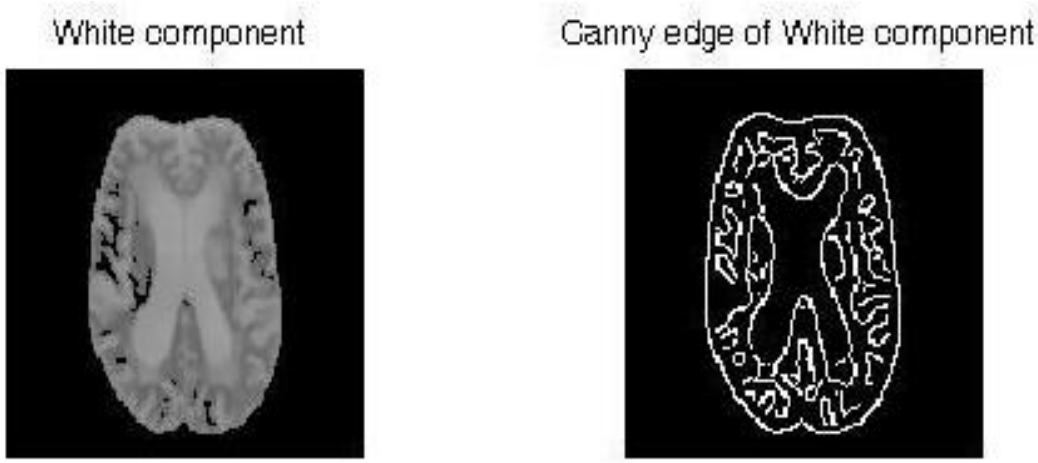


Figure 4.6 Segmentation of white gray and csf region using Double Thresholding Algorithm

- **White Region**

Figure 4.6 shows the canny edge of white components and edge features of white component. Intensity level of white components is very high as compared to gray region and csf region.



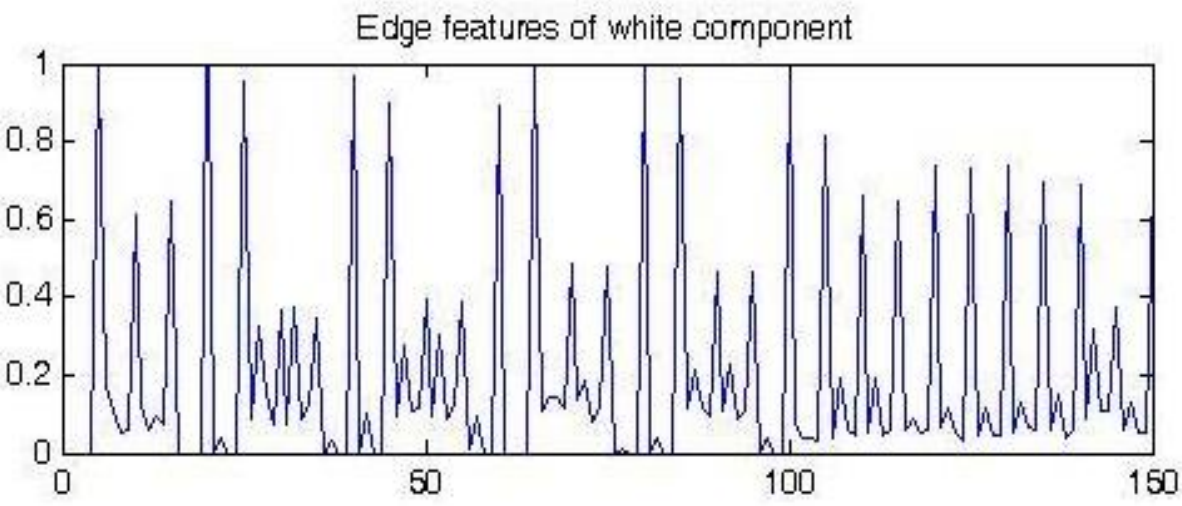


Figure 4.7 Edge features of white components

- **Gray Region**

Figure 4.7 shows the canny edge of gray components and edge features of gray component. Intensity level of gray components is medium.

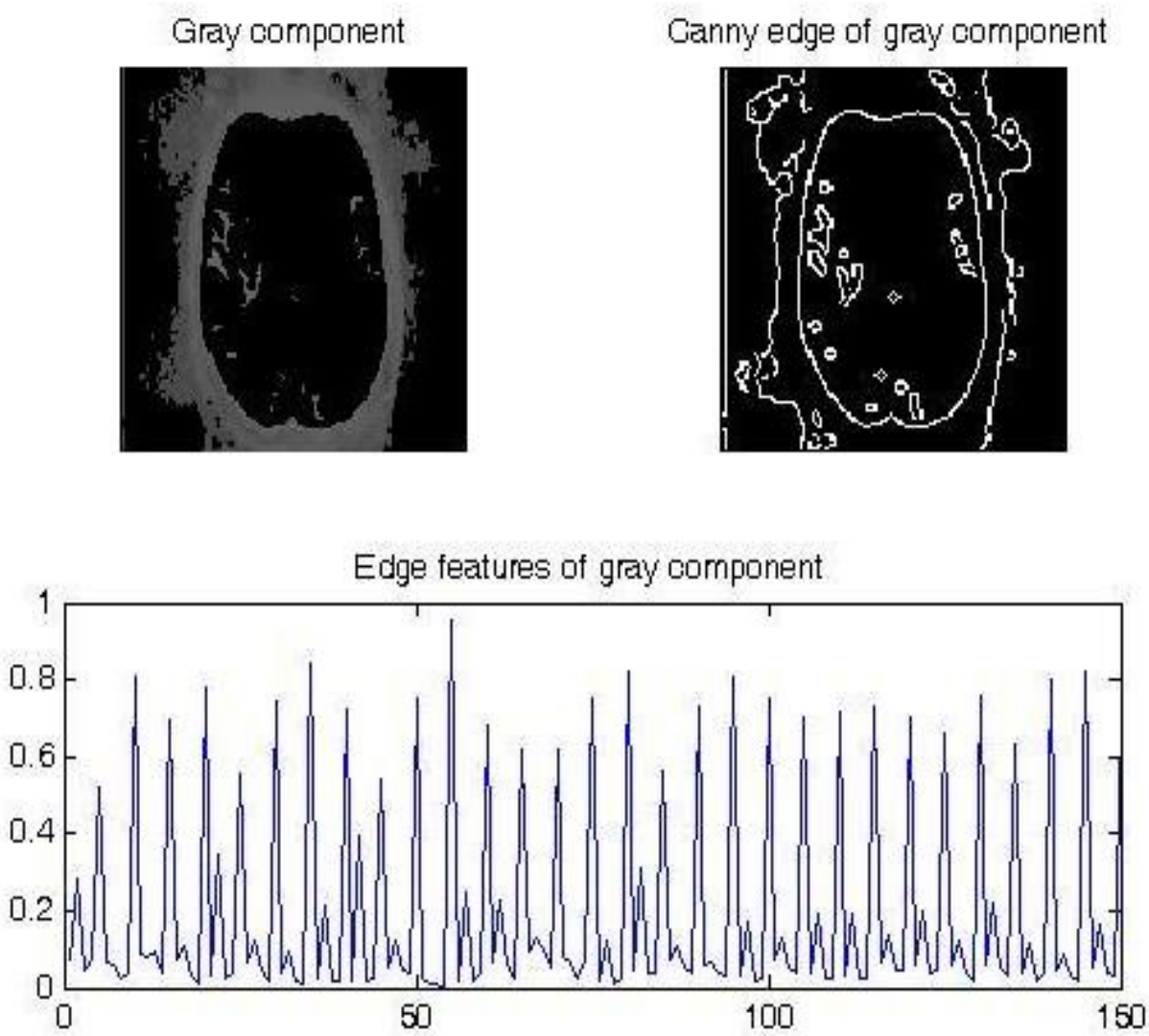


Figure 4.8 Edge features of gray components

- **Csf Region**

Figure 4.7 shows the canny edge of csf components and edge features of csf component. Intensity level of csf components is very low hence it is drawback.

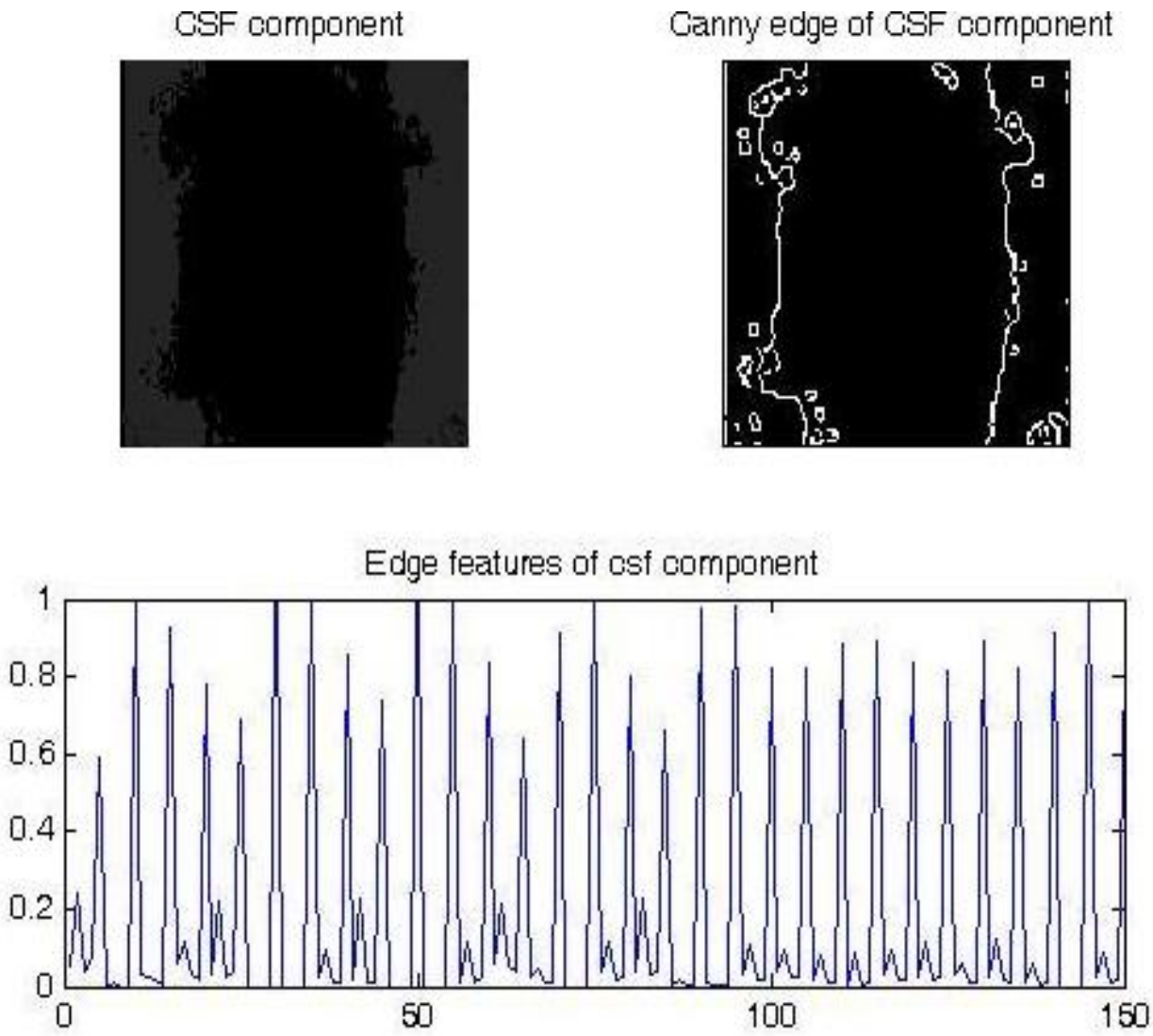


Figure 4.9 Edge features of csf components

4.3 Projection and Radon Transform

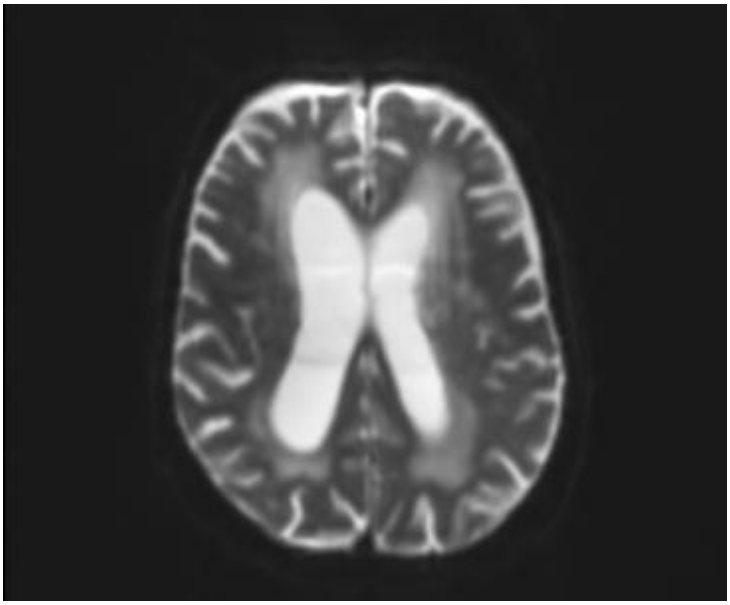
The radon transform is an integral transform for reconstruction of medical scanned images. Inverse of radon transform help to reconstruct the medical images. It reconstruct the object from projection data, it takes one dimensional fourier transform of projection data for deriving radon transform. The projection data calculate the object using two dimensional inverse-fourier transform.

In general the image formed from a single backprojection obtained at an angle θ is given by,

$f(x,y) = g(x \cos\theta + y \sin\theta, \theta)$.....(1)

Final image is formed by integrating all backprojected images.

$f(x,y) = \int_0^{\pi} f_\theta(x,y)\,d\theta$ ..... (2)



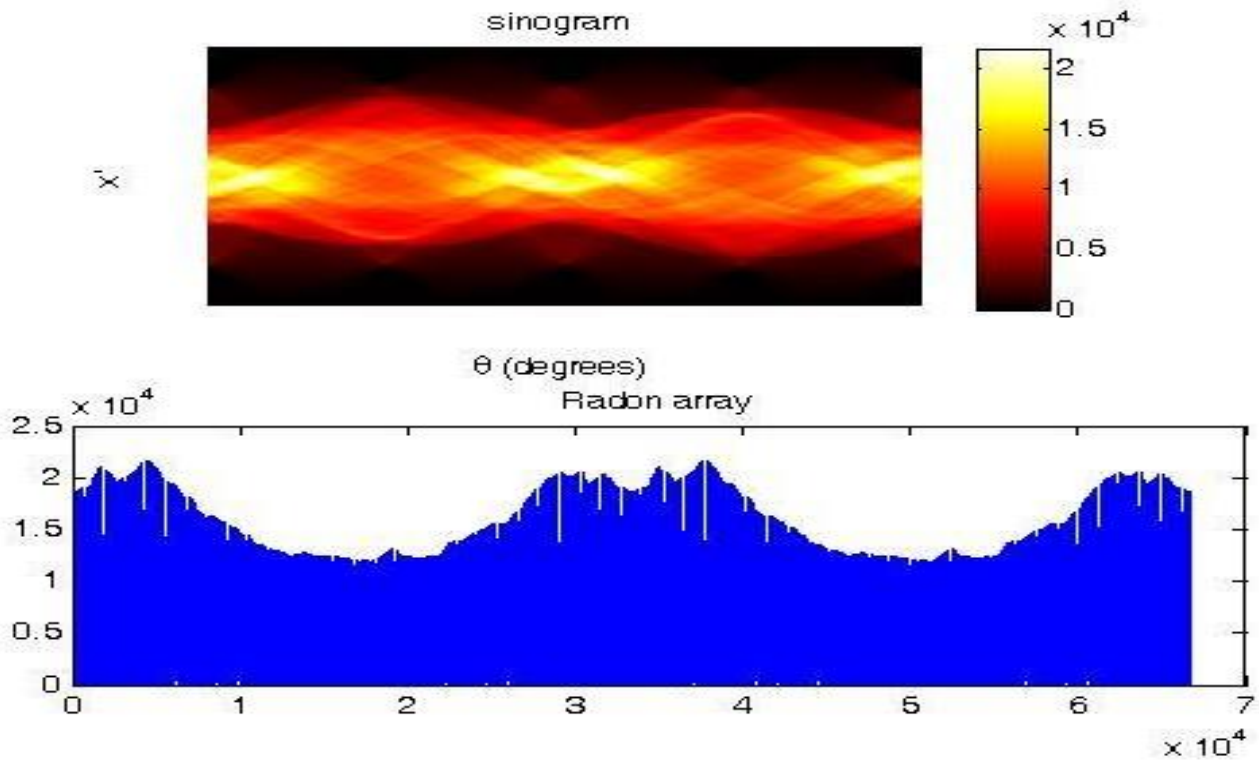


Figure 4.10 Sinogram of Input image with radon array

4.4 Performance Evaluation

K-NN classifier is most widely used classifier in image processing. If no. Of samples are large classification is much more better. In this paper K choose as a 2 i.e., taking two input images. All related images are stored into database, according to stored database k classifies the new object based on similarity index.

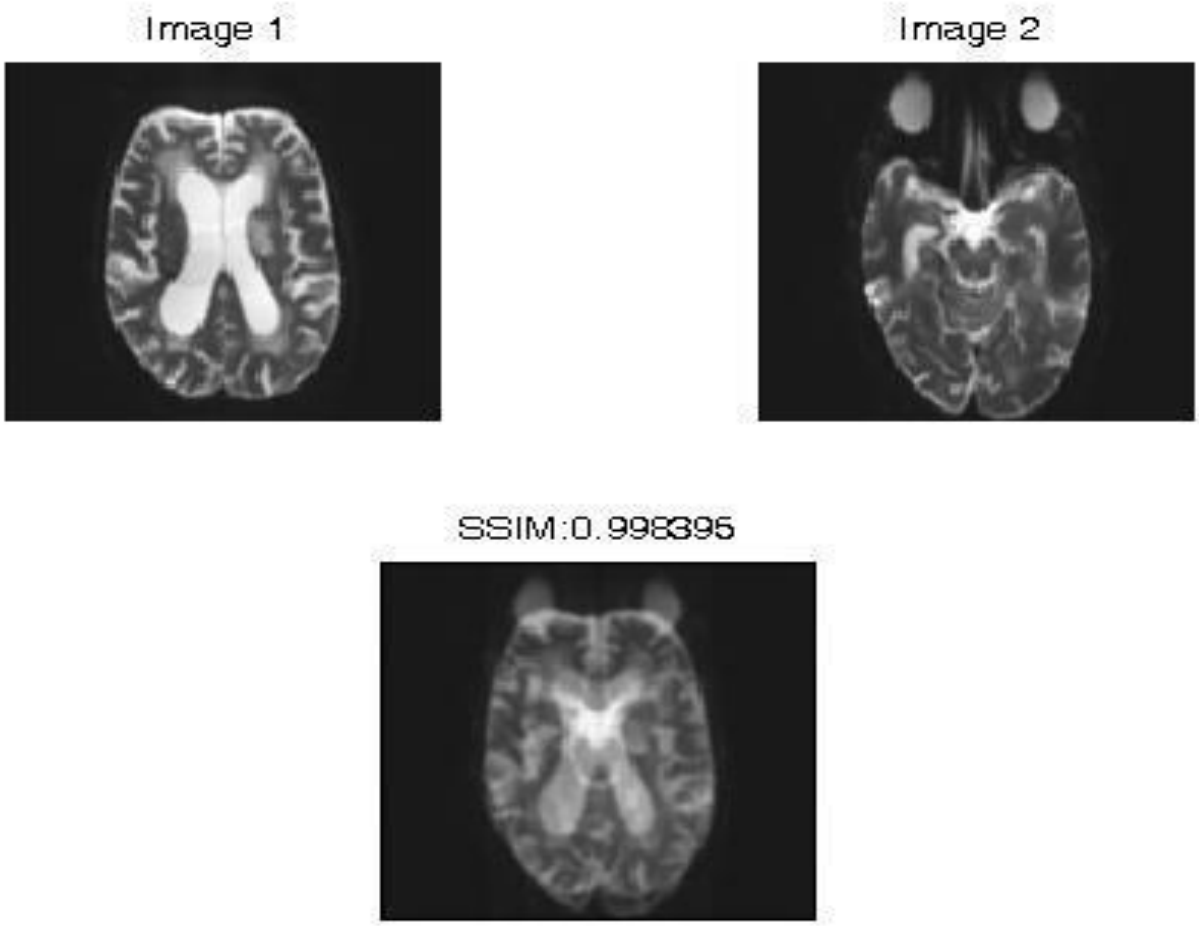


Figure 4.12 Structural similarity of image 1 and image 2

Structural similarity index (SSIM) of image obtained after substracting ‘one’ from dissimilarity in images. The two parameter are implement “Train” and “Test”. Train implement to store the images into database and test implement to check whether the images are ‘Real’ or ‘Fake’.

4.5 Results

In this experimental study we reconstruct the brain MRI images using generative adversarial network (GAN) for fast and accurate reconstruction. The proposed method suggest that GAN beat other method in qualitative validation. Table 1. Tabulates the quantitative comparison result of GAN variation with other method, overall table shows that the improved MSE and PSNR.

Table 4.1 Qualitative results (MSE and PSNR) of comparison study using different random undersampling ratios of 1D Gaussian mask.

Sr. No.	Methods	MSE	PSNR
1.	**PG**	**0.05**	**44.39dB**
2.	**PPG**	**0.05**	**45.61dB**
3.	**PPGR**	**0.04**	**47.30dB**
4.	**PFPGR**	**0.04**	**47.83dB**
5.	**GAN - White Region** **Gray Region** **CSF Region**	**0.0023** **0.0030** **0.0031**	**50.5203dB** **49.2901dB** **49.1679dB**

In order to test the quality of images in accordance to MSE (Mean square error) and PSNR (peak signal to noise ratio) we compared following DAGAN variation. (1) Pixel-GAN (PG), Pixel-Perceptual-GAN (PPG), Pixel-Perceptual-GAN-Refinement (PPGR), Pixel-Frequency-Perceptual-GAN-Refinement (PFPGR). We achieves higher PSNR (i.e., PSNR>48).

Table 4.2 Performance evaluation of images with 90% accuracy and structural similarity

Images	Actual Image	Obtained Image	SSIM
Image 1	Real	Real	0.9983
Image 2	Real	Real	0.9976
Image 3	Fake	Fake	0.9975
Image 4	Real	Real	0.9983
Image 5	Fake	Fake	0.9982

We address MSE, Peak Signal to Noise Ratio (PSNR in dB) and structural similarity, alsoevaluate qualitative visualisation of reconstructed MRI images. Table 2. shows the performance evaluation of images with 90% accuracy and structural similarity.

5.1 SUMMARY

This thesis deals with the challenges that arise in the context of image reconstruction of accelerated measurements. Established strategies from the literature, some of them (like SENSE and GRAPPA) already used successfully in daily clinical practice, are summarized in chapter 2. Afterwards, the more recent concept of iterative image reconstruction, especially in combination with nonlinear L1 based regularization terms is introduced.

While image reconstruction from randomly sampled data has been a hot research topic in the last years, little work was done to address the problem of designing pseudo-random sampling patterns. An approach is presented that uses training data to estimate the power distribution in k-space, which then leads to the design of tailored sampling patterns for specific anatomic regions.

The introduction of a new image model (TGV) that can be used as a regularizer for iterative image reconstruction of undersampled data. It is demonstrated in simulations and with in-vivo measurements that this approach effciently removes undersampling artifacts, eliminates the well known problem of staircasing and preserves fine details and sharp edges in the reconstructed images.

5.2 CONCLUSION

In this research, displayed a contingent GAN based profound learning technique for quick MRI images reconstruction and easy to find the structural similarity of images than other methods. The proposed GAN strategy has surpasses ordinary CS-MRI approaches and furthermore increase similar remaking contrasted with recently created strategies however, the preparing time has been amazingly diminished, empowering conceivable continuous application by joining with existing MRI filtering succession and parallel imaging. Peak signal to noise ratio is very much improved so that quality of image is being enhanced and also the structural similarity index of

proposed method is very much improved (SSIM = 0.9982) as compared to other methods. We can think this reenactment based examination to be meant the genuine clinical condition.

5.3 FUTURE WORK

Based on the result of this work , there are a no. of interesting point that should be the target of future research and will be investigated in second finding period. We have implemented the proof-of-concept GAN model for generating images from a very simple data distribution.

- Visualize the before and after of the Discriminator update.
- Change the activation functions of the layers and see the difference in training and generated samples.
- Add more layers and different types of layers and see the effect on the training time and the stability of the training.
- Modify the code for generating data to include data from 2 different curves
- Modify the above code to work with more complex data such as MNIST, CIFAR-10, etc.

Another remaining issue that needs to be addressed is the robustness of the reconstruction. Especially in dynamic applications, it does not seem possible to fully avoid randomly occurring non-stochastic errors in the data. Thus, when the reconstruction by parallel imaging relies on only few measured data, the erect of corrupted data on the result may be fatal. For this reason, such data must be reliably identified and removed from the reconstruction. A possible solution could result from the use of robust estimators as known from stochastics.

5.4 APPLICATIONS

Generative Adversarial Network (GAN) is applicable in wide variety of applications; few of them are described as follows.

- CS used in MRI scanning methods.
- CS used in facial recognition application.
- CS used in mobile phone camera sensors.
- Network tomography.
- Used to reconstruct 3D models of objects from images.

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