A Modified GNS Map Denoising Approach for Digital Images

Bachelor of Computer Science and Engineering

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Declaration

I hereby declare that this thesis is based on results obtained from my own work. Due acknowledgement has been made in the text to all other material used. This thesis, neither in whole nor in part, has been previously submitted to any other University or Institute for the award of any degree or diploma.

Signature of Supervisor	**Signature of the Author**
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List of Abbreviations

2-D	Two Dimensional
GNS	Global Dominant Neighborhood Structure
DNS	Dominant Neighborhood Structures
JPEG	Joint Photographic Experts Group
MSE	Mean Squared Error
PNG	Portable Network Graphics
RGB	Red, Blue, Green

Abstract

This paper proposes a new technique of noise reduction for 2D digital images. In the proposed model, for constructing a GNS map using DNS maps of central pixels we measured the intensity similarity between center pixel and its neighboring pixels within a certain window. In the proposed scheme, the intensity similarity is being calculated by using Manhattan distance equations; where the conventional GNS map approach uses Euclidean distance principle. To validate the performance of the proposed model, we consider several attacks on our tested dataset and experimental results demonstrate that the proposed model performs better than the conventional GNS map based denoising technique by exhibiting lower MSE results.

CHAPTER 01
Introduction

1.1 Motivation

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Texture Classification is the problem of distinguishing between textures, a classic problem in pattern recognition [1]. The main challenge is the development of effective features to extract from a given textured image.

1.2 Contribution Summary

The summary of the main contributions is as follows:

- Dominant Neighborhood Structure (DNS) is an approach to extract global image features for the purpose of texture classification. DNS is a feature extraction method is based on exploiting the high redundancy that exists in texture images in general and in homogeneous texture images with repetitive patterns specifically. The main contribution of this work is to modify the DNS algorithm.
- After modifying the Algorithm Different types of noise measuring technique are applied to measure which modified algorithm are more efficient.

1.3 Thesis Outline

The rest of the thesis is organized as follows:

- Chapter 02 includes the necessary background information regarding the proposed approaches of Denoising Technique.
- Chapter 03 presents the proposed Algorithm.
- Chapter 04 demonstrates the experimental results and comparison.
- Chapter 05 concludes the thesis and states the future research directions

CHAPTER 02

Background Analysis

Ever since then, a good number of denoising technique have been proposed by various researchers trying to come up with best result [2]. To denoise sparcity and multiresolution images Wavelets denoising technique is being used. This Wavelets method is published in 1995.This help to reduce noise from signal while it is storing. Wavelets algorithm rely on some threshold value like VisuShrink, SureShrink and BayesShrink. Wavelet Algorithms' limitation is these values fails to deal with Mean Square Error [3]. After that Data Adaptive Threshold technique is introduced. Hidden Markov Models and Gaussian Scale Mixtures are also popular denoising techniques [4]. In Hidden Markhov model the authors used Gaussian mixture distributions to map the wavelet coefficients as well as the correlation between the magnitudes of the wavelet coefficients in each scale on the hidden state of mixture [3]. Gaussian mixture distribution technique is described in [5]. Like above algorithms we discussed there are a number of improved and modified denoising techniques have been developed so far.

2.1 Texture Classification

Texture Classification is the problem of distinguishing between textures, a classic problem in pattern recognition [1]. As there are many very trailblazing classifiers exist, the main challenge here is the development of effective features to extract from a given textured image.

Given a texture description method, the performance of the method is often demonstrated using a texture classification experiment, which typically comprises of following steps [21]. All steps may not always be needed the order of below steps may vary:

- **Selection of image data:** Selection of image is very important. the image data and textures can be artificial or natural, possibly obtained in a real world application. the most widely used image data in texture analysis literature is probably is Brodatz (1966) textures. An important part of the selection of image data is the availability and quality of the ground truth associated with the images.

- **Partitioning of the image data into sub images**: image data are often limited in terms of the number of original source images available, hence in order to increase the amount of data the images are divided into sub images, either overlapped or disjoint, of a particular window size.
- **Preprocessing of the (sub)images:** the (sub)images may have different gray scale properties. In texture analysis the goal is to discriminate (sub)images based on texture, not on first or second order gray scale properties. Therefore (sub)images are often preprocessed to have uniform gray scale distribution, or equal first and second order statistics, by histogram equalization, for example.
- **Partitioning of the (sub)images data into training and testing sets:** In order to obtain an unbiased estimate of the performance of the texture classification procedure, training and testing sets should be independent. Different approaches can be used, including N-fold (the collection of (sub)images is divided into N disjoint sets, of which N-1 serve as training data in turn and the Nth set is used for testing), leave-one-out (each (sub)image is classified one by one so that other (sub)images serve as the training data) and holdout (the data is, preferably randomly, divided into separate training and testing sets, this can be repeated for a number of iterations for a more reliable estimate of performance).
- **Selection of the classification algorithm**. In addition to classification algorithm this may involve other selections such as metrics or (dis)similarity measures. Selection of classification algorithm can have great impact in the final performance of the texture classification procedure. No classifier can survive with poor features, but good features can be wasted with poor classifier design.
- **Definition of the performance criterion:** two basic alternatives are available, analysis of feature values and class assignments, of which the latter is used much more often. In the former the similarity of feature values between training and testing sets, or the separation of class clusters provided by the feature values, provides the basis for the quantitative performance analysis. In the case of class assignments, the items in the testing set are classified, and the proportion of correctly (classification accuracy) or erroneously (classification error) classified items is used as performance criterion.

The final output of a texture classification experiment depends on numerous factors, both in terms of the possible built-in parameters in the texture description algorithm and the various choices in the experimental setup. Results of texture classification experiments have always been suspect to dependence on individual choices in image acquisition, preprocessing, sampling etc, since no performance characterization has been established in the texture analysis literature [21].

2.2 DNS Algorithm

DNS is defined as Dominant Neighborhood Structure which is a feature extraction method is based on exploiting the high redundant that exists in texture images in general and in homogeneous texture images with repetitive patterns [1]. In Fig 1. Traditional DNS Algorithm are shown. In this process a 2D Digital image are taken and make them to grayscale images.

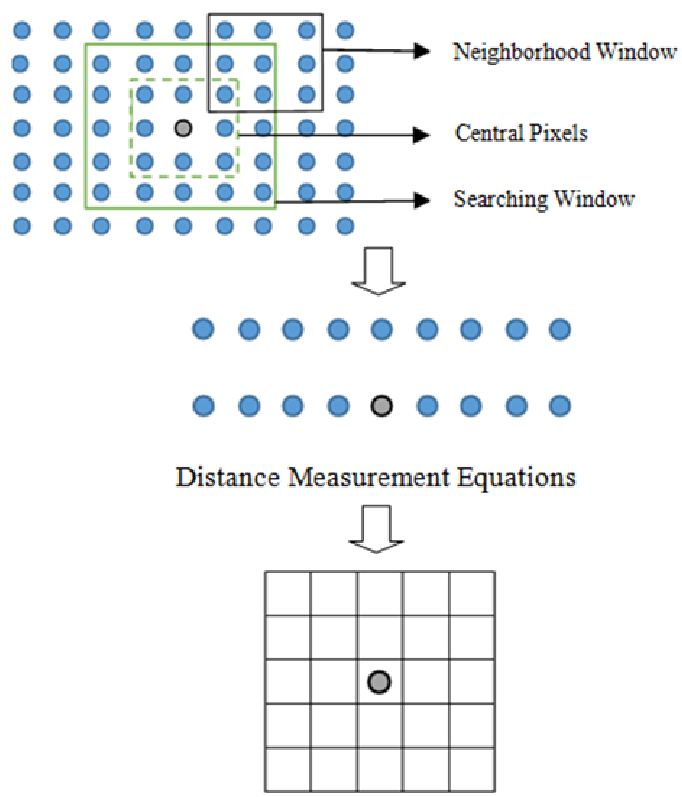


Fig 1. Traditional DNS Algorithm

Search window as well as Neighborhood window are selected through the image and both are in squared shape. Window size The maximum classification accuracy is reached when the search window is 21*21 and the neighborhood size is 13*13 or larger [2]. Search window Si and a selected image pixel i located at the center of the search window is computed. To compute the intensity similarity between a given image pixel and any of its neighboring pixels within the square search window Euclidean Distance Equation in Equation (1) are used [2]. After measuring the distance value between two points previous value of specific points are replaced by obtained value. After the completion of measuring distance and replace those points when the ultimate resulted image has got it will be more noise free than the previous one.

CHAPTER 03

Proposed Model

3.1 Overview

Fig 2. demonstrates the block diagram that represents the implementation procedure of the proposed model of denoising technique.

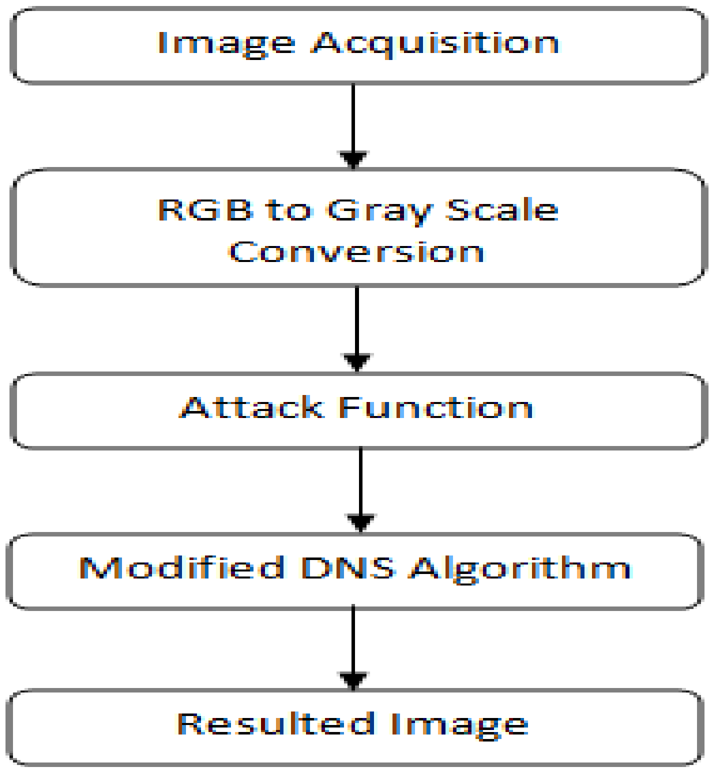


Fig 2. Proposed Denoising Algorithm

A detailed description of the proposed algorithm has been given in different sub-sections:

3.2 Image Acquisition

It is the process of acquiring an image as the input of the proposed model. Fig 3. shows a sample image that has been taken under consideration as an input image for the proposed algorithm.

Fig 3. Sample Image for the proposed model

3.3 RGB to Gray Scale Conversion

After the completion of the image acquisition technique the input image then converted to gray scale. The reason behind converting the RGB image to gray scale is, the color of the RGB image is not stable as a result the currently available solutions sometimes fail to provide a better accuracy rate [6, 7]. Furthermore, gray scale based processing techniques provide advantages in case of implementing mathematical equations as the pixel values range between 0 – 255. Fig 4. displays the converted image from RGB to gray scale.

Fig 4. Resulted Image after RGB to Gray Scale Conversion

3.4 Attack Function

Attack function is the section in which several types of noise have been added to the original image (Gray Scale Image). The list that contains the types of noises that have been added, one after another, to the original image:

1. Gaussian Noise
2. Localvar Noise
3. Poison Noise
4. Salt and Paper Noise
5. Speckle Noise

The noises have been added to the image one after another and then the resulted image after the noise addition technique has been given as the input for the modified DNS algorithm. After that we have added another type of noise and the same process goes on. Detailed descriptions of the noise that have been added to the original image and the amount of noise that have been reduced from them, by using the modified DNS algorithm, have been given in the result analysis section.

3.5 Proposed Denoising Algorithm

The proposed algorithm of this paper considers the intensity similarity of a given image pixel to its surrounding pixels within a certain local image neighborhood called search window, then the high texture redundancy implies that the pixel neighborhood similarity will be the same for most, if not all, image pixels. The input images have been segmented by using two different windows. One is Search Window and another is Neighborhood window. Fig 2. shows the block diagram of the modified DNS algorithm and Fig 5. shows the workflow of getting desired proposed denoising algorithm.

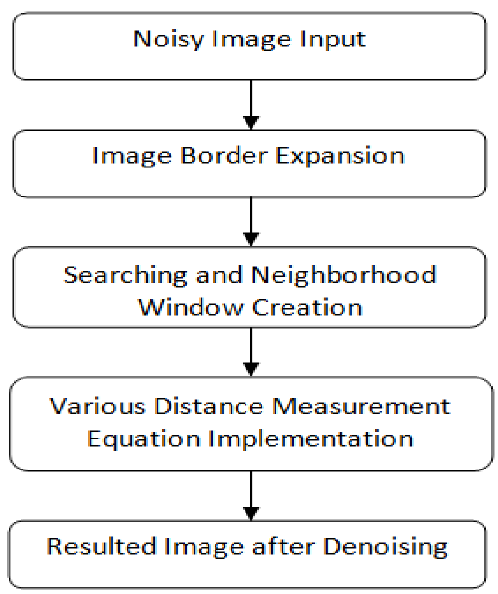


Fig 5. Block Diagram of Workflow of Proposed Denoising Algorithm

3.5.1 Noisy Image Input

The image is basically the image that we are obtaining after the Attack Function.

3.5.2 Image Border Expansion

In this section the border of the input image has been extended. The reason behind extending the border is, at the beginning of the sliding process the searching window would have ignored the pixels that are situated at the edge of the image, in order to provide space to the neighbor window. As a result, the accuracy of the DNS algorithm would have degraded. Therefore, the pixel values from the upper and lower most row and from the left and right most column have been copied and then the image has been resized by adding one extra row and column at the top and bottom, left and right most position of the image respectively. Fig 6. exhibits the image border expansion technique for some sample pixel values.

173	173	170	176	178	177	167	167
173	173	170	176	178	177	167	167
174	174	164	176	180	174	158	158
181	181	159	177	193	177	161	161
193	193	171	189	204	190	176	176
205	205	198	203	209	209	193	193
221	221	214	215	222	226	209	209
221	221	214	215	222	226	209	209

Fig 6. Example Image Border Expansion Technique

3.5.3 Searching and Neighbor Window Creation

Windows can be different in size. We have done several experiments on this and selected the optimal size so that we can get best possible results. We have selected some center pixels to compute the intensity similarity between a given set of pixels and any of its neighboring pixels within the square search window. The size of the search window and the neighborhood size are two important parameters that affect both the classification accuracy and the computation time needed to build the representative neighborhood structure map.

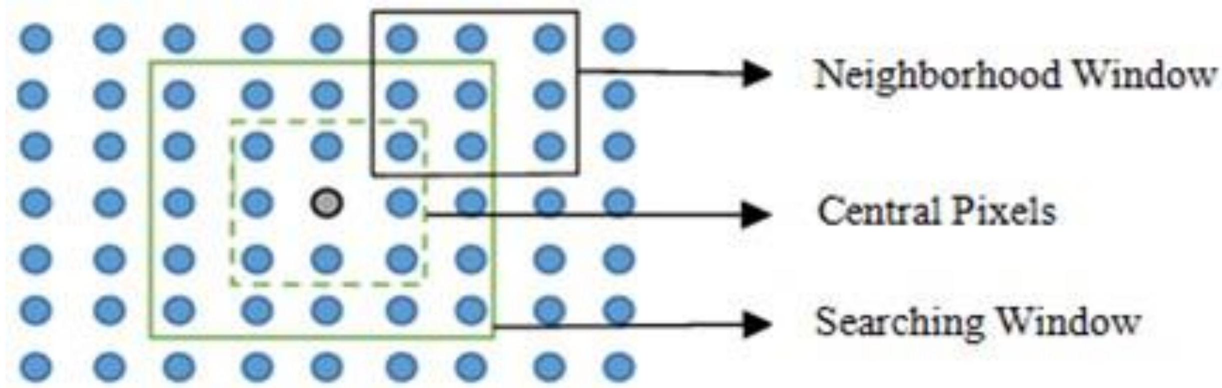


Fig 7 Construction Procedure of DNS Map

The optimal size for both was determined experimentally based on the obtained classification accuracy after applying our method to images that contain various scales of texture details. Our resulting classification accuracy as the size of both the search window and the neighborhood is varied. Observe that a classification accuracy of more than 94% is achieved even with the smallest size of both search window and neighborhood. We took our Searching window is (5*5) square size and take our neighborhood window (3*3). Both are in square shape. The spacing interval between pixels used to build the neighborhood structure maps is an essential factor that affects the resolution at which the dominant neighborhood similarity is captured. To generate a representative neighborhood structure at a given scale of resolution, it is important to have sufficient number of neighborhood structure maps generated from pixels covering the whole texture image and located at a certain spacing interval from each other. It is experimentally found that the representative neighborhood similarity map can be reliably generated from only small subset of image pixels having a size that varies according to the spacing interval, the texture image size and the noise level in case of a noisy image. To determine an optimal value of the spacing interval and hence the size of the necessary subset of image pixels, a range of intervals were selected and the resulting texture features extracted from the obtained representative neighborhood structure map were used in classification experiments. Fig 7. shows a visual representation of the searching window and the neighborhood window.

3.5.4 Various Distance Measurement Equations Implementation

We have used several distance measurement equations to calculate the difference between the selected central pixels and neighborhood pixels and set the result on the center of the neighborhood window. In order to illustrate the repeated neighborhood similarity of texture image pixels, we computed the similarity between various selected texture image pixels and their neighboring pixels within a search window. We refer to the generated map of similarity at any given pixel as the neighborhood structure map. The neighborhood structure map indicates the degree of similarity between the pixel under consideration and its neighboring pixels within the search window.

The list contains the distance measurement equations that have been used in this research in order to establish the proposed denoising technique.

Euclidean Distance Equation:

$$d(x,y) = \sqrt{\sum_{i=1}^{i=n}(x_i - y_i)^2} \tag{1}$$

Squared Euclidean Equation**:**

$$\mathrm{d}(\mathrm{x},\mathrm{y}) = \sum_{\mathrm{i}=1}^{\mathrm{i}=\mathrm{n}}(\mathrm{x}_\mathrm{i}\text{-}\mathrm{y}_\mathrm{i})^2 \tag{2}$$

Manhattan Distance Equation:

$$d(x,y) = \sum_{i=1}^{i=n}|x_i - y_i| \tag{3}$$

Canberra Distance:

$$d(x,y) = \sum_{i=1}^{i=n}\frac{|x_i - y_i|}{|x_i + y_i|} \tag{4}$$

Bray Curtis Distance Equation:

$$d(x,y) = \frac{\sum_{i=1}^{i=n}|x_i - y_i|}{\sum_{i=1}^{i=n}|x_i + y_i|} \tag{5}$$

CHAPTER 04

Experimental Results

Fig 2. demonstrates a block diagram of our proposed model. It demonstrates how the algorithm was set up. We used Dominant Structure Algorithm for de-noising our noised images. Here Some Distance Equation are applied to calculate the distance between center pixel and neighbor pixels and checked which one gives us better result.

We take a 2D digital image with no noise so that we can check later how much noise is reduced. We make it to grayscale image. We make the image to following noised image Fig 8. shows some images that contains the noises that have been discussed at the Attack Function section. As mentioned above all these 2D images are imposed certain amount of noise and later we have used our proposed denoising techniques upon these images. Gaussian Noise is the values of each pair of time are identically distributed as well as statistically independent. Poison Noise is also called Photon noise and it depends on measurement of light, photon direction and quantized nature of light.

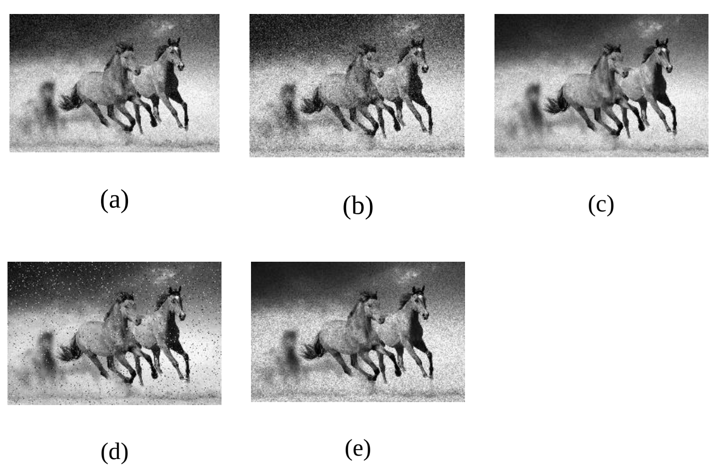


Fig 8. (a) Gaussian Noise Image, (b) Localvar Noise Image, (c) Poison Noise, (d) Salt and Pepper Noise Image, (e) Speckle Noise Image.

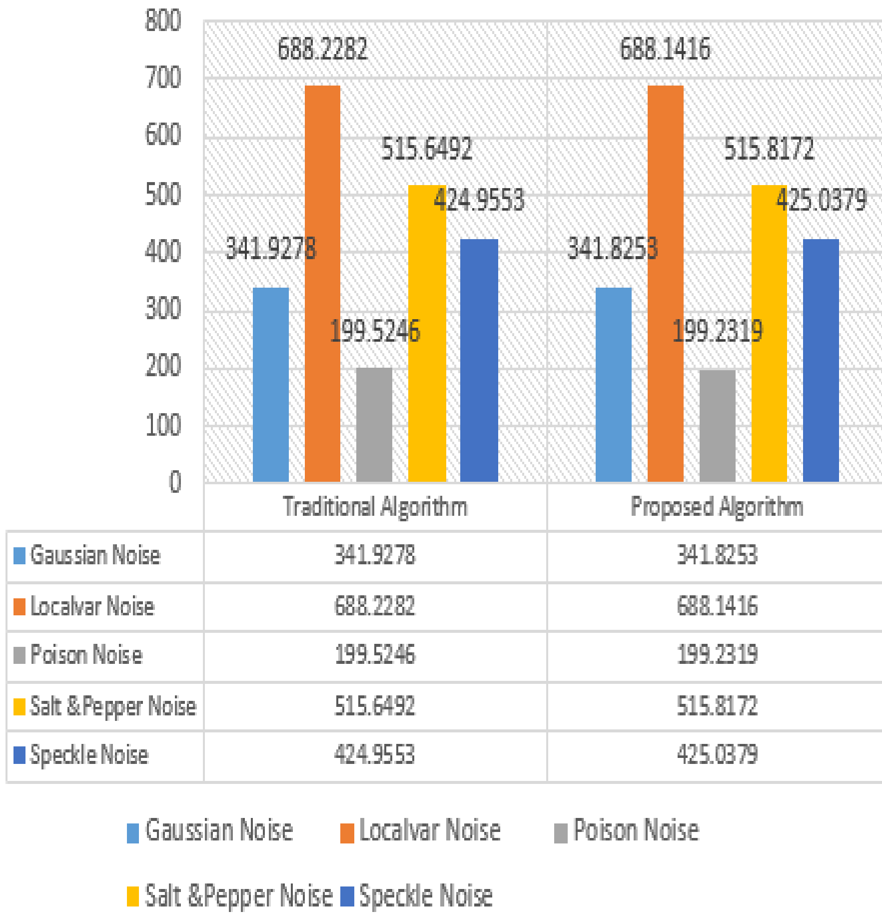


Fig 9. Chart on Traditional DNS map algorithm and our Proposed Algorithm.

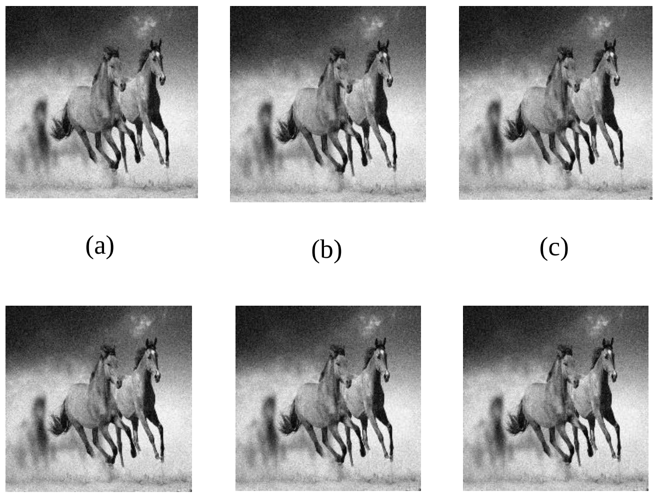
In Fig 8. (d) Salt and Pepper noise was added. This type of noise can be scattered in images as white or black or both pixels. It is also called 'Impulse Noise' and it can be caused to an image due to sharp and sudden disturbance in image signal. Speckle noise is imposed upon Fig 8. (e) image and it represented on image by random values which is multiplied by pixel values of that image. In medical literatures this noise is called as texture [8].

Table 1 : Symbol Table

Symbol	Definition
x	Pixel which is considered as center pixel.
y	Pixels of neighboring window.
n	Total pixels of window

Fig 9. shows the comparison clearly between our proposed denoising algorithm and Traditional DNS map algorithm. Our proposed algorithm shows visible change to reduce noise from images of our dataset. Experiment on Different Noised Image are described on different section below.

4.1 Experimental Analysis on Gaussian Noised Image



(a) (b) (c)

(d) (e) (f)

Fig 10 (a-f). Algorithm Implemented On Gaussian Noised Image

In Fig 10 we implement Euclidean Distance (a),Squared Euclidean Distance(b),Manhattan Distance(c), Canberra Distance(d), Bray Curtis Distance(e),Cosine Correlation (f) Distance on Images where Gaussian Noise areadded. After comparing those images with image we get Mean Square Errors are given in Table 2.

Table 2 : MSE on Gaussian Noised Image

Euclidean Distance	341.9278
Squared Euclidean Distance	341.8709
Manhattan Distance	341.8253
Canberra Distance	344.5472
Bray Curtis Distance	344.5472
Cosine Correlation Distance	344.5819

4.2 Experimental Analysis on Localvar Noised Image

(a)

(b)

(c)

(d)

(e)

(f)

Fig 11 (a-f). Algorithm Implemented on Localvar Noised Image

On Localvar noised image DNS Algorithm is implemented and Mean Square Error is 688.2282(a) and in Fig 11. (b), (c), (d),(e),(f) images are being implemented with modified DNS algorithm where Squared Euclidean Distance, Manhattan Distance, Canberra Distance, Bray Crutis Distance and Cosine correlation Distance equation are used respectively and here are Mean Square Error are 688.2374(b), 688.1416(c), 690.882(d), 690.882(e), 90.9352(f).

Table 3 : MSE on Localvar Noised Image

Euclidean Distance	688.2282
Squared Euclidean Distance	688.2374
Manhattan Distance	688.1416
Canberra Distance	690.882
Bray Curtis Distance	690.882
Cosine Correlation Distance	690.9352

4.3 Experimental Analysis on Poison Noised Image

These images give following data given below:

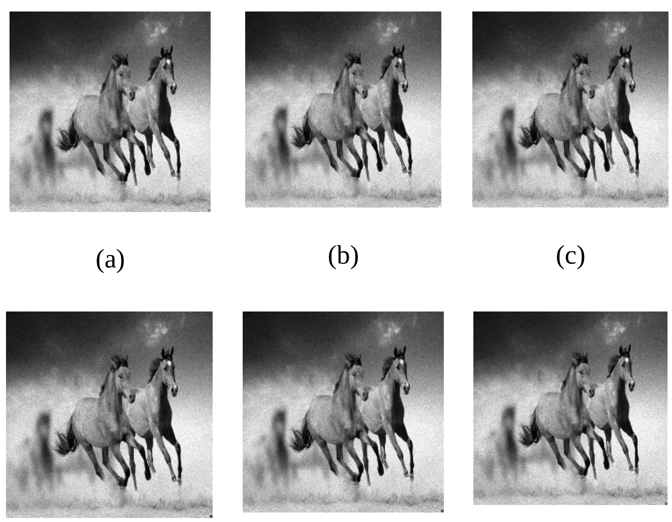
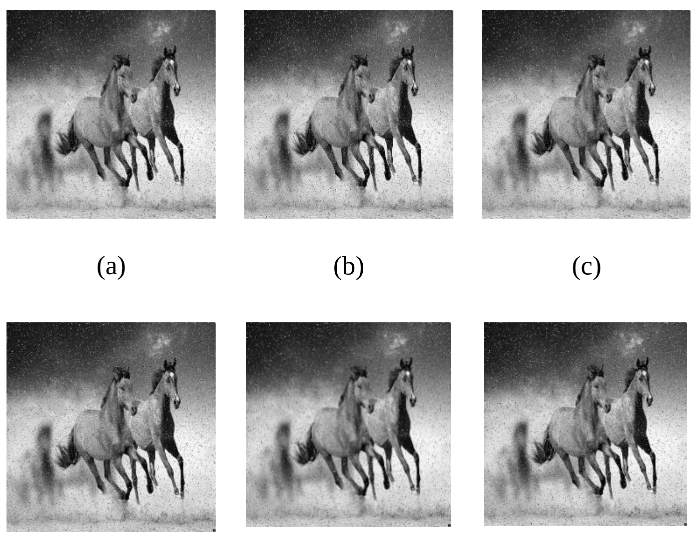


Fig 12 (a-f). Algorithm Implemented On Poison Noised Image

Table 4 : MSE on Poison Noised Image

Euclidean Distance	199.5246
Squared Euclidean Distance	199.4041
Manhattan Distance	199.2319
Canberra Distance	202.0622
Bray Curtis Distance	202.0622
Cosine Correlation Distance	202.1166

4.4 Experimental Analysis on Salt & Pepper Noised Image



(a) (b) (c)

(d) (e) (f)

Fig 13 (a-f). Algorithm Implemented On Salt & Pepper Noised Image

Table 5 : MSE on Salt and Pepper Noised Image

Euclidean Distance	515.6492
Squared Euclidean Distance	515.8149
Manhattan Distance	515.8172
Canberra Distance	518.4634
Bray Curtis Distance	518.4634
Cosine Correlation Distance	518.5454

4.5 Experimental Analysis on Speckle Noised Image

(a) (b) (c)

(d) (e) (f)

Fig 14 (a-f). Algorithm Implemented on Speckle Noised Image

Table 6 : MSE on Speckle Noised Image

Euclidean Distance	424.9553
Squared Euclidean Distance	425.0442
Manhattan Distance	425.0379
Canberra Distance	427.6667
Bray Curtis Distance	427.6667
Cosine Correlation Distance	427.716

4.5 Validate Improvement On Proposed Denoising Algorithm

In Table 7. it can be noticed that the proposed algorithm provides better results in case of Gaussian Noise, Localvar Noise and Poison Noise. Additionally, the distance measurement equations that have been utilized in this algorithm show different MSE results.

Table 7 : A Comperative Study After Imposing Different Noises and The Results of The Proposed Algorithm In Terms Of Various Distance Measuement Equations

Noise Type	Distance Measurement Equation	MSE Result
Gaussian Noised Image	Euclidean Distance	341.9278
	Squared Euclidean Distance	341.8709
	Manhattan Distance	341.8253
	Canberra Distance	344.5472
	Bray Curtis Distance	344.5472
	Cosine Correlation Distance	344.5819
Localvar Noised Image	Euclidean Distance	688.2282
	Squared Euclidean Distance	688.2374
	Manhattan Distance	688.1416
	Canberra Distance	690.882

	Bray Curtis Distance	690.882
	Cosine Correlation Distance	690.9352
Poison Noised Image	Euclidean Distance	199.5246
	Squared Euclidean Distance	199.4041
	Manhattan Distance	199.2319
	Canberra Distance	202.0622
	Bray Curtis Distance	202.0622
	Cosine Correlation Distance	202.1166

A very close observation proves that the Euclidean Distance, Squared Euclidean Distance and Manhattan Distance measurement techniques exhibits better results by providing minimum MSE value in comparison with the other distance measurement equations that have been discussed before. In order to validate the improvements, we have considered the above mentioned three equations as "Set A" and the other three equations: Canberra Distance, Bray Curtis Distance and Cosine Correlation Distance as "Set B". The average MSE values for Set A are 341.8747, 688.2024 and 199.3869 whereas the average MSE for Set **B** are 344.5588, 690.8997 and 202.0803 for Gaussian Noise, Localvar Noise and Poison Noise respectively, as shown in Table 8.

Table 8 : Comperative Study Between SET A and SET B Equations Based On MSE Rate

Type Of Noise	Set A Average MSE Rate	Set B Average MSE Rate
Gaussian Noise	341.8747	344.5588
Localvar Noise	688.2024	690.8997
Poison Noise	199.3869	202.0803

Therefore, it can be concluded that the equations of Set **A** plays more significant role in comparison with the equations of Set B in case of noise reduction from our tested dataset, because the average MSE rate is lower in Set A. Moreover, among the equations within Set **A** all three of them provide almost similar MSE rate (Table 7), but among them the suggested equation provide more desired MSE result in comparison with the others. From Table 7. it is visible that the MSE value of Manhattan Distance measurement equation is 341.8253 whereas it was 341.9278 and 341.8709 for Euclidean and Squared Euclidean Distance calculation equation respectively. As a result, it is visible that the proposed model of DNS algorithm, which includes the Manhattan distance measurement equation, is the optimal format for noise reduction from 2D digital images, for DNS algorithm. Additionally, two other types of noises have been added to the tested images in order to examine the results. In the above table (Table 8) it is visible that the chosen noises are Salt and Paper noise and Speckle Noise and a comparative result shows that the proposed model gives significantly improved results by providing lower MSE rate. Furthermore, another fact that has been noticed is Canberra and Bray Curtis Distance measuring equations are showing similar results for all the cases. Moving on, from Table 9, we can conclude that the MSE rate of the Manhattan Distance measuring equation is almost 2.5 less than the other equation as a result the proposed format of this paper of DNS algorithm can be suggested as the most optimal method of noise reduction technique by using the DNS approach.

Table 9 : A Comperative Study On MSE Rate For Salt & Pepper Noise And Speckle Noise

Noise Type	Distance Measurement Equation	MSE Result
Salt & Pepper Noise	Manhattan Distance	515.8172
	Canberra Distance	518.4634
	Bray Curtis Distance	518.4634
	Cosine Correlation Distance	518.5454
Speckle Noise	Manhattan Distance	425.0379
	Canberra Distance	427.6667
	Bray Curtis Distance	427.6667
	Cosine Correlation Distance	427.7160

CHAPTER 05

Conclusion and Future Work

5.1 Conclusion

In this study the noise reduction technique that has been implemented is based on constructing a GNS map using DNS algorithm. In which the difference between the central window pixels and the neighborhood window pixels were calculated by using Manhattan Distance based distance measurement technique. In this research while calculating the differences, several distance measurement equations have also been implemented and a comparative study has been shown among them. Which is based on the amount of noise that has been reduced from the images after adding some specific types of noises. The experimental results show that the proposed model of denoising images, by using the Manhattan distance equation, is capable enough to provide visible improvement by reducing sufficient amount of noise from noisy dataset by providing minimum MSE rate.

5.2 Future Work

The potential future directions for research based on the results presented in this thesis can be characterized into the following sections.

5.2.1 Include More Distance Equation for Better Result

There are many other equations which is implemented on matrix and vector then calculated. If we can re-arrange those pixels into matrix so that we can implement those equations instead of measuring equation between two points it will be more precise working denoising algorithm.

5.2.2 Feature Extraction and Classification

- New texture features of an image are necessary to devise, which are robust to noise and can significantly decrease performance degradation in the distinction and also for more accuracy for finding the classifications.
- Different statistical classifiers, including both supervised and unsupervised, should be investigated and experimented.

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