SOME STUDIES ON ENHANCEMENT OF IMAGES OF HISTORICAL IMPORTANCE

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SOME STUDIES ON ENHANCEMENT OF IMAGES OF HISTORICAL IMPORTANCE

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(2K14/PHD/IT/04)

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2022

DECLARATION

I hereby declare that the thesis "Some Studies on Enhancement of Images of Historical Importance," which I will submit to the Department of Information Technology at Delhi Technological University, Delhi, in order to fulfill the requirements for the award of the degree of Doctor of Philosophy, is an authentic record of my own work completed under the supervision of Prof. S. Indu. The thesis has not been submitted either in part or whole to any university or institute for the award of any degree or diploma.

Place: DTU, Delhi Date: JYOTI SWARUP (2K14/PHD/IT/04)

CERTIFICATE

This is to certify that the thesis entitled "Some Studies on Enhancement of Images of Historical Importance" being submitted by Jyoti Swarup to the Department of Information Technology, Delhi Technological University, Delhi, for the award of the degree of Doctor of Philosophy, is a record of bonafide research work carried out by him under my guidance and supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted to any other university or institute for the award of any degree or diploma.

Supervisor Prof. S. INDU Professor Department of Electronics and Communication Engineering Delhi Technological University, Delhi

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It has been an incredible and thrilling trip working on my thesis, and I am obliged to recognize a few individuals who helped this journey succeed.

Thank you, God, for giving me the strength to keep going on the right path and for all the people around me who make my life more meaningful and happier.

This thesis work has been an exciting and amazing journey and I am indebted to acknowledge a few people who made this journey successful.

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New Delhi, 2022

Jyoti Swarup

ABSTRACT

Restoration of heritage artifacts such as murals and famous paintings of the past is intended to be used for various purposes. Historical images give us an insight into our culture. It preserves and archives old historical documents, manuscripts and inscriptions like palm leaves. It helps to inform and enrich the general public of our culture and civilization. It assists scholars in their research and adds to cultural development. There is a lot of importance of mural images in our Indian culture. Our ancient temples are full of stories depicted by beautifully carved murals on the walls and ceilings of these temples. The paintings and murals are an easy means of understanding ancient stories at a glance.

Digital archive of historical images lays a foundation of preserving, restoring and digitizing images of cultural importance. Murals and sculptures have been an integral part of our culture for thousands of years. A Mural image is any bit of work of art painted or sculpted straightforwardly on a wall, roof, or other perpetual surfaces. Indian Heritage sites are known for their rich content of heritage in various forms; especially India is known for its uniqueness and cultural highlights. They are prone to get deteriorated due to several inevitable reasons like exposure to climate changes or frequent touching by spectators leading to chipping or loss of paint, formation of cracks and color distortions in murals. Hence, restoring these ancient artifacts digitally is a challenging task.

Many researchers have conducted studies of historical images in order to preserve and restore them and several techniques are used to enhance degraded historical images. It is found that existing algorithms of image processing are not compatible with historical images due to limited source of the data, complex degradation pattern, ground truth and subjective nature of enhancement. In this thesis, different methodologies are proposed to enhance degraded historical images. Each algorithm is designed in such a way that it overcomes the limitation of existing methods for image enhancement. This thesis work is primarily based on the challenges found in historical images and the proposed mechanisms to overcome these challenges. A thorough study and comparative analysis of several existing techniques for image enhancement and restoration is conducted. The entire study can be categorized as an examination and identification of multiple goals that are divided into three main groups. Each problem is approached by putting up a unique model for its resolution.

The major problem with mural images or other historical images is of poor contrast due to poor lighting conditions in which the images might have been captured or due to ageing of images. There is a loss of information in both the cases of under exposed and over exposed images. To overcome this challenge two models are designed. Each model efficiently enhances the poor contrast image. While enhancing the contrast of an image, already enhanced region of an image becomes oversaturated and loses the details within an image. Thus, in model 1 a slight washed-out effect was observed which was further improved in model 2 by proposing two different algorithms. Use of fuzzy logics made the algorithms dynamically adaptive in nature. The contrast of overall image is enhanced in such a way that under exposed areas are enhanced with different values of gamma and over exposed areas in the image are enhanced with some different value of gamma. Histogram spread is used to compare the results of contrast enhancement using other state-of-the art methods and proposed methods. It indicates that proposed methods produced more promising results.

Existing edge detection methods are complex to implement and fail to produce satisfactory results in case of noisy images. A noise in an image tends to make it look low-quality image or cluttered with probably undesired elements. Concept of Finite State Machine is explored and Cellular Automata is deployed to design an efficient edge detection algorithm which is less complex and less time consuming due to parallel processing. Some transition rules are applied to simultaneously update the values of each cell in Cellular Automata which further provides the edges present in noisy and cluttered images. Cellular computing uses logic gates to perform operations so it is computationally simple and fast due to parallel processing.

Partial Differential Equations (PDE) based inpainting methods depend highly upon the surrounding information around the target region to interpolate the values in missing region and are prone to high visual inconsistency. Patch based methods give poor result when it fails to find patch in surrounding to image inpainting region. Target region or the missing region which needs inpainting undergoes the speeded up robust features (SURF) extraction process to describe the features present in the neighborhood of missing area. The proposed method reconstructs the image in a way that looks reasonable to human eye with high accuracy and maximum similarity with ground truth images. The results indicate that the proposed method is efficient enough to interpolate the pixel values in a defected region without depending upon its adjacent pixels for interpolation.

RESEARCH PUBLICATIONS

International Journals

- Swarup Jyoti, and Indu Sreedevi. "DWT based historical image enhancement technique using adaptive gamma correction." Journal Of Algebraic Statistics, 13.1 (2022): 654-664. (ESCI, UGC-CARE)
- Jyoti Swarup, Indu S, "MSB based Cellular Automata for Edge Detection," International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-8 Issue-9, July 2019. [SCOPUS INDEXED].

International conference papers

- 3. Jyoti Swarup and S Indu, "Edge detection method based on Cellular Automata," published in International Conference on Contemporary issues in Science, Engineering & Management, (ICCI-SEM-2017), 18 19 Feb 2017 at Gandhi Institute for Technology, Bhubaneswar, Odisha, India (Best Paper Award)
- 4. Jyoti Swarup and Indu S, "Inpainting Using Surf Descriptors," published in 1st International Conference on Signal Processing, VLSI and Communication Engineering 2019 held at Delhi Technological University, Delhi, March 28-30, 2019.

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LIST OF ABBREVIATIONS

| APLTAutomatic Piccewise Linear TransformationACOAnt Colony OptimizationAGCWDAdaptive Gamma Correction with Weighted DistributionATAffine TransformTHETraditional Histogram EqualizationAWMHEAutomatic Weighting Mean-Separated Histogram EqualizationBFBacterial ForagingBSVDBlock-Based Singular Value DecompositionCACellular AutomataCIELABCommission Internationale De L'EclairageDSWTDiscrete Stationary Wavelet TransformDWTDiscrete Wavelet TransformDCRGCDynamic Contrast Ratio Gamma CorrectionFISFuzzy Inference SystemHEHistogram EqualizationJPEGJoint Photographic Experts GroupMSBMost Significant BitMSBCAMost Significant Bit Cellular AutomataMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTSStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma CorrectionXORExclusively-OR | Abbreviation | Definition |
|---|--------------|---|
| AGCWDAdaptive Gamma Correction with Weighted DistributionATAffine TransformTHETraditional Histogram EqualizationAWMHEAutomatic Weighting Mean-Separated Histogram EqualizationBFBacterial ForagingBSVDBlock-Based Singular Value DecompositionCACellular AutomataCIELABCommission Internationale De L'EclairageDSWTDiscrete Stationary Wavelet TransformDWTDiscrete Wavelet TransformDCRGCDynamic Contrast Ratio Gamma CorrectionFISFuzzy Inference SystemHEHistogram EqualizationMSBMost Significant BitMSBCAMost Significant Bit Cellular AutomataMSEMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCASignal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSIMStructural Similarity Index MeasureSIMStructural Similarity Index MeasureSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | APLT | Automatic Piecewise Linear Transformation |
| ATAffine TransformTHETraditional Histogram EqualizationAWMHEAutomatic Weighting Mean-Separated Histogram EqualizationBFBacterial ForagingBSVDBlock-Based Singular Value DecompositionCACellular AutomataCIELABCommission Internationale De L'EclairageDSWTDiscrete Stationary Wavelet TransformDWTDiscrete Wavelet TransformDCRGCDynamic Contrast Ratio Gamma CorrectionFISFuzzy Inference SystemHEHistogram EqualizationJPEGJoint Photographic Experts GroupMSBMost Significant BitMSBCAMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRSeeded Up Robust FeaturesSIMStructural Similarity Index MeasureSSIMStructural Similarity Index MeasureSSIMStructural Similarity Index MeasureSIMStructural Similarity Index MeasureSIMStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | ACO | Ant Colony Optimization |
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| CIELABCommission Internationale De L'EclairageDSWTDiscrete Stationary Wavelet TransformDWTDiscrete Wavelet TransformDCRGCDynamic Contrast Ratio Gamma CorrectionFISFuzzy Inference SystemHEHistogram EqualizationJPEGJoint Photographic Experts GroupMSBMost Significant BitMSECAMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | BSVD | Block-Based Singular Value Decomposition |
| DSWTDiscrete Stationary Wavelet TransformDWTDiscrete Wavelet TransformDCRGCDynamic Contrast Ratio Gamma CorrectionFISFuzzy Inference SystemHEHistogram EqualizationJPEGJoint Photographic Experts GroupMSBMost Significant BitMSBCAMost Significant Bit Cellular AutomataMSEMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRSeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSSIMStructural Similarity Index MeasureSKFSpeeded Up Robust FeaturesSKFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | СА | Cellular Automata |
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| MSBMost Significant BitMSBCAMost Significant Bit Cellular AutomataMSEMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTSpeeded Up Robust FeaturesSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | HE | Histogram Equalization |
| MSBCAMost Significant Bit Cellular AutomataMSEMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | JPEG | Joint Photographic Experts Group |
| MSEMean-Square ErrorMRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | MSB | Most Significant Bit |
| MRMMultiple Regression ModelPDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | MSBCA | Most Significant Bit Cellular Automata |
| PDEPartial Differential EquationsPCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | MSE | Mean-Square Error |
| PCAPrincipal Component AnalysisPSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | MRM | Multiple Regression Model |
| PSNRPeak Signal-To-Noise RatioSIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | PDE | Partial Differential Equations |
| SIFTScale-Invariant Feature TransformSURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | PCA | Principal Component Analysis |
| SURFSpeeded Up Robust FeaturesSSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | PSNR | Peak Signal-To-Noise Ratio |
| SSIMStructural Similarity Index MeasureSWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | SIFT | Scale-Invariant Feature Transform |
| SWTStationary Wavelet TransformSRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | SURF | Speeded Up Robust Features |
| SRFSpeeded Up Robust FeaturesTS MethodTakagi-Sugeno Fuzzy ModelTCGTraditional Gamma Correction | SSIM | Structural Similarity Index Measure |
| TS Method Takagi-Sugeno Fuzzy Model TCG Traditional Gamma Correction | SWT | Stationary Wavelet Transform |
| TCG Traditional Gamma Correction | SRF | Speeded Up Robust Features |
| | TS Method | Takagi-Sugeno Fuzzy Model |
| XOR Exclusively-OR | TCG | Traditional Gamma Correction |
| | XOR | Exclusively-OR |

Chapter 1

INTRODUCTION

1.1 Introduction

Any piece of art that is directly painted or sculpted on a wall, roof, or other permanent surface is called a mural. Indian heritage sites are renowned for their abundance of historical artifacts; the country is particularly well-known for its distinctiveness and cultural attractions. [1, 2].

Ancient mural images are subjected to a variety of distortions caused by environmental factors, temperature and humidity variations, contamination of painted surfaces, and human stupidity in failing to maintain the monuments without realizing their significance [3]. Over time, some of them have faded, while others have cracks and dirt patches growing over them. Our heritage provides many stories of the ancient age, the Cultural Heritage. Hence, such images provide information about our past. It helps us know our history and traditions and



Figure 1.1 Examples of mural images

enables us to develop an awareness about ourselves. In , some examples of mural images are illustrated in Figure 1.1

Digital archive of historical images lays a foundation of preserving, restoring and digitizing images of cultural importance [4, 5]. Murals and sculptures have been an integral part of our culture for thousands of years. They are prone to get deteriorated due to several inevitable reasons like exposure to climate changes or frequent touching by spectators leading to chipping or loss of paint, formation of cracks and color distortions in murals. Hence, restoring these ancient artifacts digitally is a challenging task. The digitizing process must not harm the artwork, and damage could easily occur by excessive handling and irradiation by high-intensity light sources. The enormous work of recording, preserving, and disseminating India's cultural legacy continues to be difficult even with the government's and many individuals' committed efforts. Due to the presence of large missing regions and degraded visual quality in mural images, it becomes difficult to create its 3D models to reconstruct large damaged regions in heritage structures. Mural images are noisy and consists of faint and broken lines. To remove spurious noises and preserve edges various image enhancement techniques exist. Image enhancement in heritage preservation can be utilized for heritage restoration in addition to enhancing image quality for easier post-processing.

Digital image is a representation of a finite set of picture elements, known as pixels, in two dimensions. It is described by the f(x,y) mathematical function. The pixel value of every given point in the image is given by the value of (x,y) at that place. An image's dimensions are determined by its pixel array. When an image is digitalized, it suggests that the digital image is a rough representation of the real scene.

Digital Image Processing focuses on developing a computer system that is able to perform processing on an image. The input of such computer system is a digital image and the system process input image using efficient algorithms, and gives an image as an output. Image Enhancement is a major step in image processing. It is an approach for transforming a degraded image into an improved image for analysis. Image Enhancement is application specific [6-8].

There are three different types of processing that are applied to an image. They are categorized as low-level process, mid-level process and high-level process as illustrated in Figure 1.2

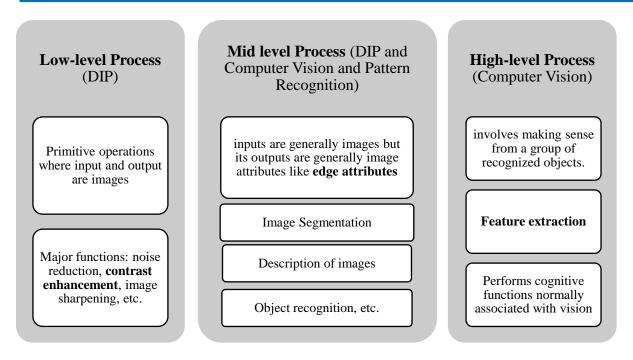


Figure 1.2 Different levels of digital image processing

1.2 Image Processing Tools

Image processing is a process to achieve desired aim by processing an image using certain mathematical operations and manipulations. Some of the basic image processing tools are filtering, blurring, thresholding, edge detection, feature extraction and region growing.

1.2.1 Edge Detection

The process of edge extraction involves identifying any discontinuities or changes in brightness within a picture in order to discern an object's contour. Many computers vision and digital image processing systems maintain significant structural aspects of an image by using the critical edge detection stage [9-13]. The detection of edges can be done mathematically in numerous ways. Basically, these methods apply some smoothing filters and compute the image's gradient in both axis. The gradient-based and Laplacian-based approaches to edge identification fall into two major groups.

1.2.2 Contrast Enhancement

Contrast is an essential element in qualitative assessment of an image [14-16]. It is the difference in luminance of two surfaces which makes different objects distinguishable from each other as well as the background. Contrast stretching develops the contrast of an image by distributing the pixel intensities to extent to a desirable range of values. Many algorithms

are developed for accomplishing contrast enhancement and used in solving image processing problems.

1.2.3 Image Inpainting

Digital Image inpainting is the process of reconstructing lost, deteriorated or degraded information of digital images and videos by using the information of surrounding areas [17-19]. Image inpainting finds its place in numerous applications of computer vision and image processing. Repairing photographs and restoration of old films to remove scratches and defects is being done since ages. Inpainting or interpolation involves application of sophisticated algorithms to remove defects and reconstruct the image in a non-detectable manner. The objective for image inpainting is not to recover the original image, but to create some image that has a close resemblance with the original image. Image inpainting can be used in cinema and photography for removing defects like scratches, dust spots from images (called deterioration).

1.3 Fundamental steps in Digital Image Processing

Image Acquisition: This represents the initial digital stage of image processing. After that, scaling and color conversion are used to transform the image into digital format. First of all, images are captured with the help of an image acquisition device, light, focal lengths play an important role in improving the quality of the image.

Image Enhancement: Digital image enhancement is the technique of converting an image to produce further outcomes that are appropriate for display or multiple image analysis. Image enhancement basically improves the visual quality or lighting of an image, removes unwanted artifacts in an image. The goal of image enhancement is to accentuate certain features, enhance details, improve contrast, reduce noise, and rectify imperfections, making the image more visually appealing and informative. It involves applying a set of operations or algorithms to modify pixel intensities or other image attributes to achieve desired enhancements, such as sharper edges, clearer textures, or better color representation.

Image Restoration: Using techniques like noise reduction, deconvolution, image inpainting, etc. depending on the degree of deterioration, image restoration is the process of taking a noisy or defective image and repairing the imperfections. Image restoration techniques aim to reverse or reduce these degradations, ultimately yielding an image that is closer to the original or ideal representation.

Colour Image Processing: Understanding both color perception and the physics of light is necessary for color image processing. It involves employing a variety of methods and algorithms to process, improve, examine, or work with color or multi-channel representations of images.

Image compression: It includes rescaling the size and resolution of images in order to develop certain functionalities and operations. Reducing duplicate and unnecessary data does this. It may lose less or be lossy. The primary objective of image compression is to minimize the amount of data required to represent an image, making it more efficient for storage, transmission, and processing, especially in applications where bandwidth or storage capacity is limited.

Morphological processing: The morphology or shape of features in an image is manipulated by a series of non-linear processes. It brings out the components and tools for extracting useful shapes and representations.

Segmentation: An image is divided into a group of homogeneous, non-overlapping areas using image segmentation, a classic image processing task. To process each component of an image separately, it requires splitting it up into smaller components. It is among the most challenging steps in it.

Object recognition: It is the task of finding and identifying objects in an image. It detects and identifies each subject in the image and gives them a label suitable for it, assigned by the descriptor algorithm.

1.4 Challenges in Historical image

Our cultural heritage finds its roots some hundreds of years ago. Humans started to communicate through the drawings and murals painted on rocks or walls. Historical images have a rich history about the past; thus, their study enriches modern people with insight about the past. However, in the course of their study and management, a number of challenges abound [20, 21]. Murals are the art pieces generally found on the walls of public places. They are prone to get deteriorate by constant touching and mishandling by visitors and archeologists to an extend that they tend to break. Murals present in the interiors of a building might face problem of illumination. Badly lit areas tend to result in poor contrast images posing a challenge in image acquisition. Changing weather also effects the condition of murals [22, 23].

Figure 1.3 shows some examples of degraded mural images. Several challenges are identified in Historical images and challenges are listed below [24]:

- Aging effect in mural paintings
- Faint and broken lines on murals
- Missing patterns or regions of murals
- Badly illuminated images
- Varnish oxidation results in low visual appearance of paintings
- Noisy and blurred image
- Presence of cracks in digitized paintings
- Undesirable painting patterns such as stains, crevices and artifacts
- Manuscripts distorted with show-through effects, uneven background color etc.



Figure 1.3 Some examples of degraded mural images

1.5 Problem Definitions

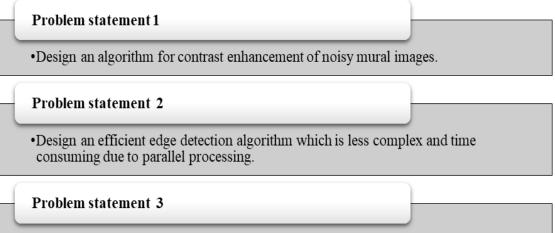
In literature, numerous techniques are available for enhancement of images. This thesis attempts to address some major limitations in existing methods used for enhancement of historical images in order to preserve them and proposes new algorithms for an efficient and reliable system for image enhancement. Illumination and lighting also play an important role while taking pictures of these artifacts of historical importance. The poorly lit surroundings

will result in dark and low contrast digital images while over exposed lighting conditions may give high contrast and bright images. Many algorithms like Histogram Equalization, contrast stretching, gamma correction are developed for accomplishing contrast enhancement and used in solving image processing problems. There is loss of information in both the cases of over exposed and under exposed images. Virtual restoration of degraded historical images requires multiple image processing operations to obtain enhanced images preserving the structure, texture and colors of the original image.

This thesis work is primarily based on mural images. Moreover, this thesis discusses importance and reconstruction of mural images. The complete study can be classified as an investigation and analysis of three related problems enlisted below:

- Lack of methods which provide pre-processing of digital image like contrast enhancement of degraded mural images.
- Existing edge detection methods are complex to implement so they have large processing time. These methods tend to produce non-satisfactory results for noisy images which have cluttered background.
- Lack of methods for automatic selection of best patch based on image content for patch based inpainting methods.

1.6 Research Problems And Thesis Overview



•Design an image inpainting algorithm for automatic selection of similar patch based on image content of missing region.

Figure 1.4 Problem statement in thesis and proposed models

The core objective of the thesis is to design algorithms that reconstructs degraded images efficiently to obtain maximum information from the digital image to make the image more visually appealing and easier to interpret. To address the issues of image enhancement of historical images, three research problems are made and algorithms are designed to resolve these research objectives. The complete study can be classified as an investigation and identification of several objectives, which are segregated as three major categories of interrelated problems. Every problem is addressed by proposing different model of the solution as shown in Figure 1.4. To overcome the above unique challenges and to achieve the stated objectives, the following research objectives were formed.

The thesis organization is illustrated in Figure 1.5 and organized as follows:

Chapter 1: INTRODUCTION

This chapter begins with a contextual review of image processing. The study of mural images and its importance are discussed. A brief theory of image processing and the traditional mechanisms along with basic terminologies of image processing are discussed in all the sections of this chapter. The last section presents the organization of the thesis.

Chapter 2: LITERATURE REVIEW

This chapter presents a brief study of the existing techniques present in the literature used for image enhancement, edge detection and inpainting. The work done specifically for mural images is discussed and analyzed in detail.

Chapter 3: Contrast Enhancement of historical images

This chapter presents two novel contrast enhancement model based on the discreate wavelet transform, stationary wavelet transforms and adaptive fuzzy gamma correction method.

(a) Discrete Wavelet Transform based historical image enhancement technique using adaptive gamma correction

(b) Stationary wavelet transforms (SWT) based Mural image enhancement using adaptive Fuzzy gamma correction

Chapter 4: MSB based Cellular Automata for Edge Detection

In this chapter, an approach is proposed for edge detection scheme of mural images using 2D Cellular Automata. The comparative analysis is done to validate the efficiency of proposed method.

Chapter 5: Inpainting Using Surf Descriptors

This chapter presents a technique of image inpainting to reconstruct the missing and damaged regions of a mural image.

Chapter 6: Conclusion and future work

In this chapter, findings of the proposed work are presented in summary. Also, future work is discussed.

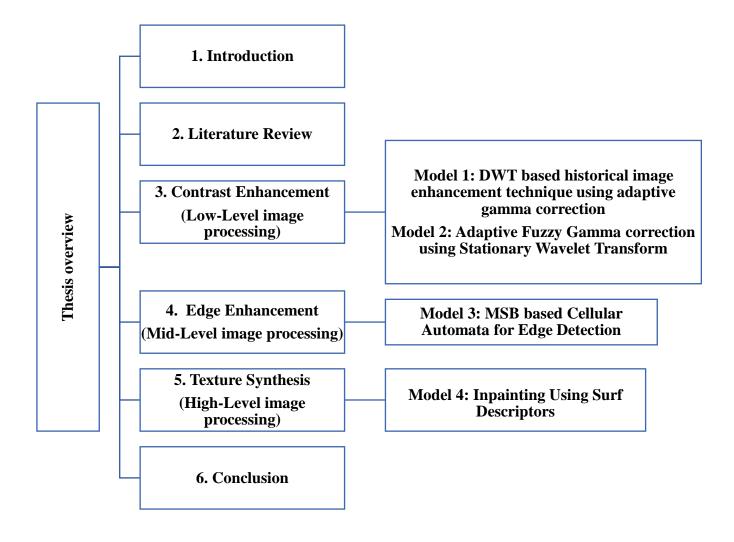


Figure 1.5 Thesis organization

Chapter 2

LITERATURE REVIEW

This chapter has a prime focus on the literature survey of image processing algorithms of images of historical importance. Several contrast enhancements, edge detection and image inpainting algorithms are devised for enhanced results and optimum performance in the field of image processing. In this age of digital storage and recreation, several technologies enable us to capture these monuments and manuscripts in digital form. Image acquisition, image enhancement and image restoration are the key features of modeling and representing tangible heritages.

In recent time researchers and scientists are interested to design algorithms for the enhancement and restoration of historical images to make them suitable for the purpose of various studies [4, 25-28] on historical monuments, culture and heritage. To analyze our designed algorithms, we have studied and analyze existing algorithms and compared proposed with the state-of-the-art algorithms. Before designing the objectives of the thesis, we have studied and investigated the available existing methods and then developed algorithms to serve many purposes, and all the algorithms present in this work performed well. It can be observed after investing existing algorithms that image enhancement [29-31], edge detection [11, 32, 33] and image inpainting [17, 18] play an essential role in digital image processing as it is a crucial pre-process in the field of artificial intelligence, object recognition and pattern recognition.

In [34] Ghorai et al. proposed an interactive algorithm for coherent image completion that would be useful for the paintings containing repetitive patterns under constrained environment where user needs to mark the target or damaged region together with the source or texture region. A significant amount of research has been carried out for analysis of damaged historical manuscripts and inscriptions. When the difference between the text and background is very small, the text extraction problem becomes challenging. Text detection, localization, and text extraction from pictures of inscriptions and manuscripts have all been approached in a number of ways [20, 35, 36].

Automatically detecting the cracks in photographs of monuments explores a new area of digital inpainting introducing several inpainting algorithms and automatic mask detection. Variational inpainting [37-39] focuses on completion of geometrical structure of an image. It involves solving of partial differential equations. In [16], Bertalmio modified the previously developed PDE-based inpainting methods. Texture synthesis [1, 34, 38, 40-44] i.e., producing new instances of texture from a smaller sample is capable of inpainting images that contain several texture areas. It fills larger regions more accurately. Image quilting [43, 45] is one of the first patch-based texture synthesis algorithms developed by Efros and Freeman. In literature it is discovered that the standard method for exemplar-based inpainting involves using matching blocks from the known region of the same image to gradually fill in the blocks on the inpainting region's boundary [39, 46] and the example based algorithms are ideal to inpaint the region of complex texture such as grass, cloud, wall or sky.

In case of uneven background, the use of low-pass Wiener filter, and contrast adaptive binarization for segmentation gives better extraction of text from background [35]. Napa Sae-Bae et. al. [47] presented an image denoising method known as adaptive BSVD method. It is found that these techniques alone cannot improve the visibility of the degraded images. In Laurence et. al. [26] a new approach to document enhancement was given, combining two potent noise-reduction procedures from recent times. First, the Total Variation architecture served as the foundation. Second, Non-local Means was the foundation for that stage. The computing difficulty of the Non-Local Mean filter is dependent on the patch size and window sizes.

Ntogas et al. [36] proposed binarization procedure consisted of five discrete steps in image processing, for different classes of document images. The primary contribution of this paper was to provide a straightforward and reliable binarization process for historical manuscript images that had already been pre-filtered. Simulation results are also shown. Badekas et al. [48] proposed a new method which the estimates the best parameter values for each one of

the document binarization techniques and also the estimation of the best document binarization result of all techniques.

2.1 Inpainting based Literature

In the recent time, researchers have developed several systems for image inpainting. The existing methods of image inpainting are listed in section 2.1.

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|---|--|---|--|
| [49] | Navier-stokes, fluid dynamics, and image and video inpainting | To constantly propagate isophote lines from the outside into the area that has to be painted, the method makes use of concepts from classical fluid dynamics. | The fluid dynamics method is derived directly from the Navier- Stokes equations. | Dynamical evolution of the fluid equations and stability of solutions is not explored |
| [50] | Level lines based disocclusion | In contrast to edges, a level lines structure provides a dependable, comprehensive, and contrast-invariant representation of an image when disocclusion is applied. | Strong discontinuities may be present in the solution produced by level lines-based disocclusion, which is not achievable with PDE-based interpolation. | It is very complex method to implement and has high complexity of time and space. |
| [51] | Variational inpainting based on Euler's elastica and curvature- driven diffusion | It focuses on completion of geometrical structure of an image. It involves solving of partial differential equations. | Non-blind inpainting | Use of mathematical equations makes it computationally complex |
| [52] | Variational inpainting based method which proposed Mathematical Models for Local Non-texture Inpaintings | It involves solving of partial differential equations. | This method focuses on completion of geometrical structure of an image | Use of differential equations makes this model computationally complex |

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|---|---|--|--|
| [53] | Projection Based Image and Video Inpainting Using Wavelets (Variational inpainting) | Focuses on the completion of geometrical structure of an image. It involves solving of partial differential equations. | It facilitates structure reconstruction | This method is complex to implement due to use of partial differential equations |
| [41] | Non-texture Inpainting by Curvature-Driven Diffusions | This method makes use of level-lines and other equations for inpainting | Preserves structural information | Complex mathematical equations involved |
| [16] | PDE based inpainting where Strong- continuation, contrast-invariant inpainting with a third-order optimal PDE | Modified the previously developed PDE-based inpainting methods. | Non-blind inpainting method | Not capable of inpainting large regions |
| [54] | A survey on variational image inpainting, texture synthesis and image completion | Producing new instances of texture from a smaller sample is capable of inpainting images that contain several texture areas. | It fills larger regions more accurately. | This method may not be able to work for images in frequency domain |
| [42] | Exemplar based inpainting done by Multiresolution sampling procedure for analysis and synthesis of texture images | Blocks on the inpainting region's edge are gradually filled in by utilizing similar blocks from the known area of the same image. | Non-blind inpainting method | Cannot inpaint an image properly if matching patch is not found in the image |
| [36] | Non-blind inpainting method for binarization of historical manuscripts | An easy-to-use and reliable binarization process | Intended for photos of historical manuscripts that have been pre- filtered. | Tested on Limited Images |
| [55] | Blind inpainting method for the detection and removal of cracks in digitalized paintings | Automatically detects the cracks in digital images by using top- hat transform | A rapid neural network with a median radial basis function is used to eliminate cracks. | In case of complex images, a cluttered crack map may lead to blurring of whole image. |

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|--|---|--|--|
| [34] | A patch based constrained Non- blind inpainting for damaged mural images | Presented a technique to digitally improve the mural images by combining the mean image with the weighted average of the original image. | Tested on mural images | It requires prior information about the damaged region |
| [40] | Partial Differential Equation (PDE) based algorithm for Structure and Texture Image Inpainting | The technique is designed to transfer geometric and photometric data from the boundary of the obscured region into the actual area. (Using isophote lines to propagate the information in the direction of minimal change) | If there are smaller missed regions, the outcomes will be favorable. | This approach will take a long time and yield subpar results if the missing regions are large. |
| [56] | A local inpainting method through Total Variational (TV) Inpainting model | Because of the isophote driven method, which makes the algorithm effective, we can quickly complete the image by identifying the line of equal gray scale values that holds the most promising information. | This algorithm can help in preserving the structural information | Imitating vast texture patches is the key challenge of this algorithm. Additionally, this technique is not able to recover Partially Degraded Image. |
| [57] | A parametric texture model based on joint statistics of complex wavelet coefficients for Exemplar-based algorithms | By utilizing matching blocks from the known region of the same image, the blocks on the boundary of the inpainting region are filled in gradually. | It produces satisfactory results only in cases where the missing region has simple structure and texture. | The sequence of filling is critical. It is impossible to synthesize the desired image if there are insufficient samples in the image. |
| [58] | Use Gibbs sampling to synthesize texture by modeling it as a Markov Random Field. | Entropy based simulation | Easy to implement | Very slow, not possible to assess when it has converged |

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|---|---|--|---|
| [59] | Pyramid-based texture analysis/ synthesis | Combine the filter response histograms at various spatial scales to coerce (make do out of necessity) a random noise image into a texture sample. | When used to extremely stochastic textures, this approach performs well. | More structured texture patterns, such bricks, cannot be well represented by the histograms. |
| [42] | Multiresolution sampling procedure for analysis and synthesis of texture images. (multi- resolution filter- based approach) | Multiresolution sampling procedure is applied to fill the texture | A huge variety of textures can be synthesized with success using this method, but only on mostly stochastic textures does the randomness parameter appear to behave in a perceptually accurate manner. | This approach generates texture images that are larger than the input, which is a downside. The synthesis algorithm assumes implicitly that all textures are tilable, which is obviously incorrect, and simply replicates the supplied texture sample to fit the needed dimensions. |
| [60] | Image Inpainting Using Wavelet- Based Inter and Intra-Scale Dependency | In order to find the wavelet and scaling coefficients, the algorithm decomposes the incomplete image with the use of wavelets. In order to apply the image inpainting procedure in the wavelet domain, the target region's wavelet coefficient and scaling are taken into account. | This uses the Wavelet Transform to preserve the texture quality and image structure by utilizing inter- and intra-scale dependencies. | Mask for regions are defined manually. |

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|---|---|---|--|
| [61] | Texture synthesis by non-parametric sampling | The method is entirely automatic and yields excellent results for texture generation. Ideal for covering a wide range of textures in areas that need painting. | The purpose of the method is to maintain the local image structure, like continuous straight lines, so that the freshly synthesized patch and the original hole outline do not visually differ. | Certain textures' tendency to periodically "slip" into the incorrect portion results in exact replicas of the original. For the neighborhood context window, this makes it difficult to discover nearby matches. By offering a larger example image, these issues can typically be resolved. |
| [62] | Cluster-based probability model for texture synthesis, classification, and compression | Cluster based Probability method to balance the texture. | Works well for large regions | Here are the three primary challenges: 1) defining a textual unit (a letter) and its context (a n- gram) for texturing 2) in building a probability distribution, and 3) in linearizing the 2D synthesis procedure. |

2.2 Edge based Literature

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|--|--|---|---|
| [63] | Edge-based image restoration | The edge information is used to direct the subsequent interpolation as well as to reconstruct a skeleton image structure in the missing areas. | A method of filling pixels that considers the orientation and proximity of edges. | Highly dependent on edge information |
| [48] | Estimation of Appropriate Parameter Values for Document Binarization Techniques | Presented a novel approach that determines the optimal parameter values for any document binarization process. | The estimation of the best document binarization result of all techniques. | May fail for complex and cluttered images |
| [64] | This paper discusses the accuracy of the Sobel edge detector. | It makes use of derivative approach by returning those edges where the gradient of the image is maximum. | It uses first derivative with simpler calculations to detect edges and easy to implement | Performs poorly on blurred or noisy images results in a greater number of discontinuities of edges |
| [11] | Comparison of Various Edge Detection Technique Major emphasis is done on Prewitt Operator | Very similar to Sobel operator | Simple to implement | Performs poorly on blurred or noisy images |
| [65] | Canny detector: A Computational Approach to Edge Detection | Tracing edges through hysteresis thresholding. It is assumed that strong edges are continuous in image. The output only includes weak edges if they are related to strong edges. | It is discovered to be the ideal edge detector. All potential edges are indicated. | Complicated and time-consuming method. For too low threshold it may falsely identify irrelevant information and for too high threshold it can miss important information. |

| Reference | Method | Techniques used | Advantages | Disadvantages |
|-----------|---|--|--|--|
| | | | | |
| [66] | Fuzzy logic reasoning strategy for edge detection in digital images | Recognizing edges in digital images without specifying a threshold value, simply by splitting an image into a 3 × 3 window. | Determination of threshold was not required for edge detection | Slow and complex method |
| [67] | Biomimicry of bacterial foraging for distributed optimization control using Bacteria foraging algorithm. | The life cycle of bacteria is divided onto four stages: (1) chemo taxis; (2) swarming; (3) reproduction; and (4) elimination and dispersal. | Produces the best answer for the optimization problem. | It avoids the fact that edges naturally occur continuously. Because it can look among the surrounding edge pixels for the next edge pixel, the BF is preferred. Because of this, Bacteria Foraging is more appealing computationally than alternative Genetic Algorithms. |
| [68] | A novel approach for edge detection using Ant Colony Optimization and fuzzy derivative technique is merged with bacteria foraging algorithm to find direction of bacteria. | A directional probability matrix obtained from Ant Colony Optimization is used to determine the direction of the bacteria's movement. | The approach is applied for identifying edges in both normal and impulse noise-corrupted images. | When applied to noisy images, it generates poor results. |
| [28] | A simple and effective histogram equalization approach to image enhancement | Histogram analysis is done in detail for enhancement. | This method's simplicity and reasonably decent results are its main advantages. | Histogram Equalization tends to over-stretch intensity levels so it introduces various artifacts such as saturation and halo artifacts. |

2.3 Contrast Image Enhancement based Literature

Image enhancement techniques can be classified into two categories 1) spatial domain related work and 2) frequency domain related work as shown in Figure 2.1; researchers have done equal amount of work in the spatial and frequency domain to improve the contrast quality of an image.

Research in many different domains has benefited from image enhancement. There are situations where photos taken with a camera or scanned documents have issues with low quality, an uneven background, and little contrast between the foreground and background [26, 69]. A number of techniques have been proposed to improve historical images [27].

In [70], the author introduced an algorithm to maintain the average brightness of the image but fails for images with high density and narrow range. The method proposed in [71] preserves the brightness and gives more probabilities to gray levels which are infrequent in medical images, but this method drops some statistical information and its recursive nature consumes more time. Zihan et al. [72] introduced an unsharp-masking technique which preserves hue of colors that enhances the contrast and spatially sharpens the texture in images.

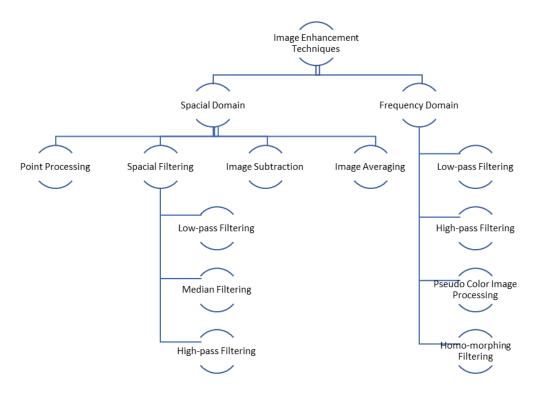


Figure 2.1 Image enhancement techniques

In [73], the author presented a soft thresholding method for denoising in 1-D signal using wavelets pyramidal filtering. Chang et al. [74] introduced an adaptive wavelet thresholding for image denoising and compression.

In [75], Pei et al. have used mixed color contrast enhancement of color images and a texture synthesis algorithm for the restoration of ancient Chinese paintings. Due to presence of large missing regions in mural images, it becomes difficult to create its 3D models to reconstruct large damaged regions in heritage structures. Principal Component Analysis (PCA) based region blending method can be used to produce seamless completion of murals. In [23], Sahay and Rajagopalan addressed geometric and photometric reconstruction of such defects by employing a tensor voting based method.

In conclusion, chapter 2 has given a thorough review of current developments in the areas of image enhancement, inpainting, and edge detection. The evolution of approaches and methodologies has been emphasized in the study, demonstrating the dynamic character of research in these important fields of image processing. Regarding image enhancement, research findings indicate that methods that improve visual quality while retaining significant semantic information are still being sought after. The delicate balance in algorithm design is necessary to address the ongoing topic of interest on the trade-off between preserving and enhancing natural characteristics. The advances in restoring missing or damaged image portions were emphasized in the literature on inpainting. Challenges such as maintaining structural consistency and handling large-scale inpainting scenarios have prompted researchers to explore innovative solutions and algorithms.

Chapter 3

CONTRAST ENHANCEMENT OF HISTORICAL IMAGES

3.1 Motivation

The sculptures and murals have a unique way of expressing age-old traditions and diversities of art that existed for many centuries. Digital imaging of historical images may have some challenges due to low-intensity lighting conditions. These images generally need correction which is done by contrast enhancement. When an image is captured in low light, it results in underexposed images. Such dark images may suffer some loss of information. Also, when images are captured in high lighting conditions it gives overexposed images. Very bright images can also suffer from loss of information. The objective of this chapter is to enhance the contrast of the overall image so as to minimize the information loss and obtain maximum information about the historical images.

This chapter addresses objective 1 to design an algorithm for contrast enhancement of mural images having poor contrast and we have proposed three methods based on wavelet transforms, which are illustrated in Figure 3.1. One method is covered in Model 1 and two methods are described in Model 2, which are as follows:

Model 1: DWT based historical image enhancement technique using adaptive gamma correction

Model 2: Adaptive Fuzzy Gamma correction using Stationary Wavelet Transform

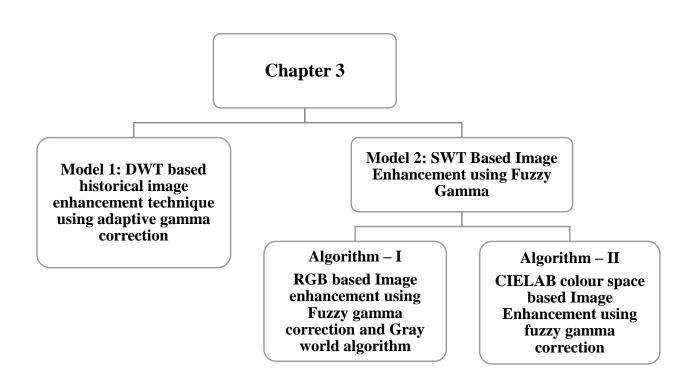


Figure 3.1 Layout of the chapter discussing different proposed methods.

3.2 Introduction

This chapter address objective 1, which is to design an algorithm for contrast enhancement of degraded mural images. Historical Images are of great significance as they depict the social and cultural heritage of a country. The sculptures and murals have a unique way of expressing age-old traditions and diversities of art that existed for many centuries. Digital restoration of historical images may undergo several defects of low-intensity lighting conditions, blurred and occluded images. Their preservation and reconstruction of damaged images are of prime importance. In this chapter, algorithms are proposed to enhance the image quality of digitally captured images of historical importance to illustrate the art and other image details clearly. Murals and sculptures are prone to get deteriorated due to several inevitable reasons like exposure to climate changes or frequent touching by spectators leading to chipping or loss of paint, formation of cracks and color distortions in mural paintings [76]. Illumination and lighting also play an important role while taking pictures of these artifacts of historical importance. The poorly lit surroundings will result in dark and low contrast digital

images while overexposed lighting conditions may give high contrast and bright images. Hence, restoring these ancient artifacts digitally is a challenging task. Virtual restoration of degraded historical images requires multiple image processing operations to obtain enhanced images preserving the structure, texture and colors [77, 78]

The digital image processing techniques are manipulations on a digital image using computers. These tasks are image acquisition, image compression, geometrical transformations, image inpainting, image restoration, image enhancement and many more [6, 8]. These manipulations help to retrieve valuable information present in the image. Spatial domain image enhancement methods manipulate the pixel values of an image [30, 79], whereas frequency domain methods manipulate the values of the coefficients of an image, as shown in Eq. (1), where, f(x,y) is input image, g(x,y) is output image and *T* is transformation function. These techniques are widely used in many applications like medical visualization, law enforcement, human-computer interfaces, artistic effects, image restoration and many more.

$$g(x, y) = T[f(x, y)]$$
⁽¹⁾

The goal of image enhancement is to either better feed other automated image processing methods or increase the information perceived by human viewers from images. Image augmentation modifies pictures to improve their depiction of minute details. Forensics, atmospheric sciences, medical imaging, and art studies are just a few of the many domains in which it is an invaluable tool for scholars. Image enhancement varies depending on the application. Enhancement techniques that are frequently employed include edge sharpening, histogram equalization, contrast enhancement, a range of filters, and more.

What works well for one class of images may not work as well for other classes when it comes to image enhancing algorithms [15, 21, 25, 28, 30, 70, 80]. An approach that works well for one problem may not work well for another. Forensic photography and video, for instance, use methods to address issues with motion blur and low resolution, whereas medical imaging gains more from sharper contrast and higher contrast. A methodology that works well for improving X-ray images might not be the ideal choice for improving satellite images captured in the electromagnetic spectrum's infrared region.

Image Negative is useful in medical imaging and can be applied to enhance white detail embedded in dark regions. For general-purpose contrast manipulation, power-law transformations are helpful. A power-law transformation with a fractional exponent is used to expand the gray levels of a dark image. Enhancing details in the image's darker areas at the price of information in the brighter areas of the higher-level values is possible with log transformation. The majority of methods work well for adjusting the gray level values of specific pixels, which in turn affects the image's overall contrast. However, their enhancement of the entire image is typically uniform, leading to unfavorable outcomes in numerous cases.

Contrast is an essential element in the qualitative assessment of an image [14]. The difference in luminance of two surfaces makes different objects distinguishable from each other as well as the background. Contrast stretching [81] develops the contrast of an image by distributing the pixel intensities to an extent to a desirable range of values. Many algorithms like histogram equalization and grayscale transformation are developed for accomplishing contrast enhancement and used in solving image processing problems. The information may be lost in both cases of under-exposed image and over-exposed image. The objective is to improve the contrast of overall image so as to minimize the information loss and obtain maximum information of the input image

3.3 Related Work

3.3.1 Histogram based Methods

Histogram equalization [15, 28, 82] finds its place in a variety of image processing applications of contrast enhancement. This method is prevalent due to its simple function and effectiveness. In [15] [13], Yeong-Taeg Kim proposed an algorithm to decompose an image and obtain two sub-images based on its mean and then apply histogram equalizations independently over these two separate sub-images, hence resulting in equalized sub-images which are bound to each other around the input mean. In [83], the author introduced an algorithm to maintain the average brightness of the image but fails for images with high density and narrow range. Coltuc et al. [84] used the image enhancement method on watermarking images which gives maximum image information with good visual quality though it may not offer any obvious choice for the desired histogram. Zihan et al.[72] introduced an unsharp-masking technique that enhances contrast and spatially sharpens the texture in images. It preserves the hue of colors in an image and adaptively controls the contrast magnification ratio.

3.3.2 Adaptive Gamma Correction based Methods

In [85], Huang et.al. proposed an adaptive method to enhance the contrast of an image using gamma correction with weighting distribution which combined the traditional gamma correction method and histogram equalization together. The adaptive gamma correction with weighted distribution (AGCWD) method fails in the absence of bright pixels as the peak intensity in the resultant image is bound by maximum intensity of input image, although it preserves the overall brightness of the image. The Dynamic Contrast Ratio Gamma Correction (DCRGC) method [86] concurrently apply TGC (Traditional Gamma Correction) and THE (Traditional Histogram Equalization) and directly sets a parameter as a ratio, though it cannot be generated automatically. Automatic Weighting Mean-separated Histogram Equalization (AWMHE) method [71] equalizes sub-histogram to accurately preserve the brightness by optimizing the threshold values through recursive function. In Conventional Piecewise Linear Transformation, some parameters are set manually making it ineffective and inefficient for real-time images. Further, Tsai et al. [87] proposed a method to alleviate these limitations by introducing a parameter free method for color images called an Automatic Piecewise Linear Transformation (APLT) function. Later, in [88] Tsai et al. proposed an algorithm for enhancement of an image based on a decision-tree, which is used to make decisions about whether the input image is dark or bright. Initially a decision is made about the type of degraded image, then piecewise linear transformation is done to improve this image. This method shows excellent performance for skin detection and visual perception, though some local features of the face image may get weak, as stated in a study conducted by Li et al.[89] in which Histogram Equalization (HE) is used in order to increase the performances of the Illumination Compensation based on Multiple Regression Model (ICR) and Affine Transform (AT) algorithms. In [90], Salah-eldin et al. suggested a method in which Histogram Equalization experiences the Gamma correction and Retinal filter's compression function (GAMMA-HM-COMP) combined together to solve the illumination effect on face images.

3.3.3 Wavelet Transform based Methods

In [87], authors proposed a frequency-domain based image enhancement algorithm, where they have included a measure of variance for each coefficient to obtain the enhanced images which are compressed with JPEG. Also, this algorithm is more suitable for those images, where direction contrast is required to improve the enhancement. In [91] Gomez et al. proposed an approach that focused on low pass band of DWT to extract the illumination from the images by using a homomorphic filtering function to obtain the illumination model making an effective approach for video sequences. The wavelet methods not only enhanced the contrast, yet improve the edges and other details to further enable the face recognition process. Zhang et.al. proposed a different color correction process for underwater images to improve the quality based on sub-interval linear transformation [92]. L channel is decomposed using Gaussian low-pass filter and optimal equalization threshold strategy enhances the contrast of image.

In 1996, the wavelet decomposition was made time-invariant with the introduction of stationary wavelet transform (SWT) [93] due to which the power of wavelet in signal denoising improved. In [94] the SWT method was applied to preprocess the microarray images for removing the random noises. In [95], the author used the Discrete Stationary Wavelet Transform (DSWT) for various wavelets at various levels to denoise an image and select the best one out of them. Non-linear thresholding techniques were applied in the wavelet domain, including hard and soft thresholding, wavelet shrinkages such as Visu-shrink (non-adaptive) and SURE, Bayes, and Normal Shrink (adaptive). In [96], the authors present a method for improving image resolution that involves interpolating both the input image and the high frequency sub-band images that are produced using discrete wavelet transform (DWT). By applying stationary wavelet transform (SWT), an intermediate stage is added to improve the edges. To separate an input image into its component sub-bands, DWT is utilized. Next, an interpolation is performed on both the input image and the high frequency sub-bands. The high frequency sub-bands acquired using SWT are used to modify the estimated high frequency sub-bands. Information loss occurs in each of the DWT sub-bands due to down sampling. SWT is therefore used to reduce this loss.

3.4 Background

3.4.1 Discrete Wavelet Transform

The conversion of a signal from spatial domain or time domain to the frequency domain using mathematical operators is called transforms [97]. Any image in the spatial domain can be represented in a frequency domain with two major components. High-frequency components relate to edges present in the image and low-frequency components correspond to smooth regions. A discrete wavelet transforms (DWT) [97-99] is used for highdimensional data analyses, such as image processing and analysis. DWT decomposes an input signal into a series of coefficients. DWT coefficients contain temporal information of the analyzed signal. One level-DWT and inverse discrete wavelet transform are represented by Eq. (2) and Eq. (3):

$$D(a,b) = \sum_{a} \sum_{b} S(a) \Phi_{ab}(n)$$
⁽²⁾

$$S = \sum_{a} \sum_{b} D(a, b) \Phi_{ab}(n)$$
(3)

where, D(a,b) defines the coefficient of DWT. Shift parameters and scale transform are denoted by a and b, respectively. Φab (n) represents the base time wavelet of the function. A bottom-up approach is used to reconstruct the original signal S by applying Inverse-DWT. The decomposition of an image using DWT is pictorially represented by Figure 3.2.

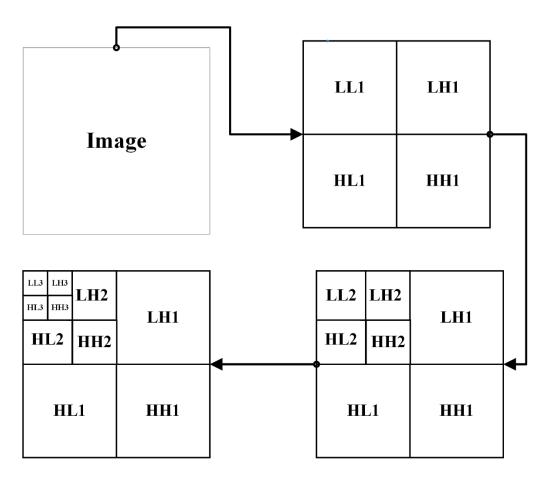


Figure 3.2 Different sub-bands obtained after the decomposition of an image using DWT.

3.4.2 Gamma Correction

A digital image (color or grayscale) created from a digital device is bound to have gamma added to it. This created bright ones too bright, but dim tones got lost in the dark, and tonal images are really hard to show. Gamma correction [85, 86, 100, 101] monitors the contrast

of an image the gamma curve behavior and is illustrated in Figure 3.3 and Figure 3.4. Varying the amount of gamma correction changes the red to green to blue ratio hence changing the brightness.

The power-law transformation of the traditional gamma correction (TGC) is represented by Eq. (4).

$$T(l) = l_{\max}(l/l_{\max})^{\gamma} \tag{4}$$

Where, l_{max} represents maximum intensity and intensity l of each pixel which is transformed as T(l). Images which are not properly corrected can look either bleached or washed out or too dark which leads to loss of image details.

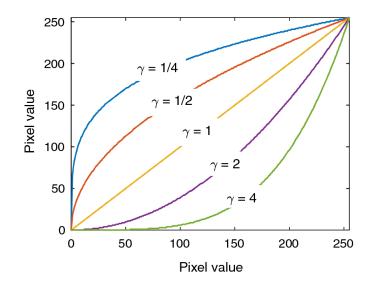


Figure 3.3 Gamma correction curve for different values of intensity.

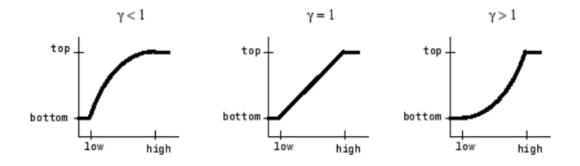
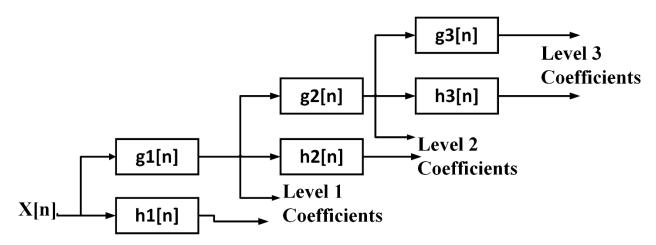
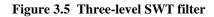


Figure 3.4 Plots showing three different gamma correction settings

3.4.3 Stationary Wavelet Transform

Another recent wavelet transform that has been used in several image processing applications is stationary wavelet transform (SWT) as shown in Figure 3.5 [102]. In summary, SWT and DWT are comparable; however, SWT does not employ down-sampling, therefore the subbands will be the same size as the original image. Because SWT uses a multi-scale decomposition approach and does not require an upper- or lower-bound sampling procedure or diminish the SWT datum post-transformation, it can aid in the retention of more information [103, 104]. Both DWT and SWT generate level coefficients over identical frequency ranges; however, whilst the length of the DWT level coefficients decreased by half with each subsequent level, the length of the SWT level coefficients stays constant at *N* samples. While SWT is only a translation-invariant wavelet transform, DWT and SWT both convert the signal into an orthogonal domain.





The property of SWT which makes it suitable for applications such as edge detection, image denoising, and image combination is its redundant representation and the fact that it is shift-invariant. In SWT, the decimation of its coefficients at each level of the transformation algorithm is omitted so more samples in the coefficient sequences are available, with equal length wavelet coefficients at each level, and hence a better detection can be performed [105]. The DWT fails to provide this feature.

3.4.4 Fuzzy system

Fuzzy logic is a field of computer science that studies manipulating imprecise knowledge by implementing approximate reasoning. Fuzzy logic allows the truth values of variables to be uncertain. It is often applied to obtain fuzzy conclusion where the truth values of variables

can lie somewhere between the values True and False. In fuzzy logic, a fuzzy inference is an inference with a fuzzy conclusion.

Fuzzy inference system is key component of any fuzzy logic system. An inference rule is a mapping from a set of premise facts to a conclusion fact.

3.4.4.1 Functional Blocks of Fuzzy Inference System (FIS)

The following five functional blocks of FIS as shown in Figure 3.6 are:

- Rule Base It contains fuzzy IF-THEN rules.
- Database It defines the membership functions of fuzzy sets used in fuzzy rules.
- Decision-making Unit It performs operation on rules.
- Fuzzification Interface Unit It converts the crisp quantities into fuzzy quantities.
- Defuzzification Interface Unit It converts the fuzzy quantities into crisp quantities.
 Following is a block diagram of fuzzy interference system.

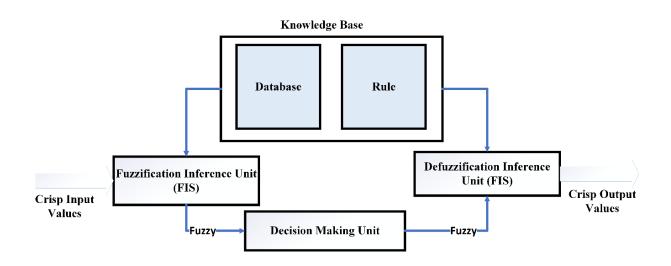


Figure 3.6 Block diagram if FIS

There are several approaches to fuzzy inference system design. For example, one approach is based on a set of rules whose premises are all combinations of the input fuzzy sets, while the conclusion is determined by the output fuzzy set. Another is based on a set of rules whose premises are all combinations of the input fuzzy sets, while the conclusion is determined by the complement (negation) of the output fuzzy set. Yet another approach is based on a set of rules whose premises are the input fuzzy sets, and whose conclusions are the complement of the output fuzzy set. To understand it properly it can be stated that fuzzy inference system uses fuzzy set theory, IF-THEN rules and fuzzy reasoning process to find the output corresponding to crisp inputs. Predicates in IF-THEN rules are connected using and or or logical connectives.

Fuzzy inference system is the first step and core part of any fuzzy logic system. Formally, a membership function for a fuzzy set A on the universe of discourse X is defined as $\mu_A: X \rightarrow [0,1]$, where each element of X is mapped to a value between 0 and 1 as represented by equation (1). This value, called membership value or degree of membership, quantifies the grade of membership of the element in X to the fuzzy set A. Here, X is the universal set and A is the fuzzy set derived from X.

$$1 > \mu_{A^{\sim}}(y) > 0$$

Following are the popular approaches to fuzzy inference system. Antecedent part of all rules remains same, they differ only in consequent part.

3.4.4.2 Mamdani Fuzzy Inference System

In 1975, [106], Mamdani fuzzy inference system was proposed by Ebhasim Mamdani to control a steam engine and boiler combination by synthesizing a set of fuzzy rules. In this setup, first of all the set of fuzzy rules are determined and the inputs are made fuzzy by using the input membership function. These fuzzified inputs are combined the find the rue strength. In the next step, rule strength and output membership functions are combined to determine the consequents of rule. Finally, a defuzzified output distribution is obtained. Figure 3.7 represents a block diagram of Mamdani FIS [107].

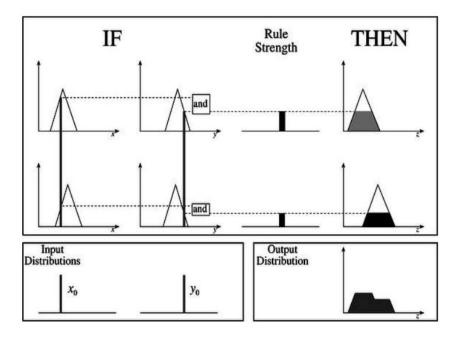


Figure 3.7 A block diagram of Mamdani Fuzzy Inference System.

3.4.4.3 Takagi-Sugeno Fuzzy Model (TS Method)

In 1985 [108], Takagi, Sugeno and Kang proposed this FIS. In this model, the inputs of the system are made fuzzy and then fuzzy operators are applied to get the output. The format of this rule is given as

IF x is A and y is B THEN
$$Z = f(x, y)$$

Here, AB are fuzzy sets in antecedents and z = f(x, y) is a crisp function in the consequent.

Defuzzification is a decision-making algorithm that is used to transfer fuzzy inference results into a crisp output. Defuzzification is realized by a decision-making algorithm that selects the best crisp value based on a fuzzy set. There are several forms of defuzzification including center of gravity (COG), mean of maximum (MOM), and center average methods. The COG method returns the value of the center of area under the curve and the MOM approach can be regarded as the point where balance is obtained on a curve. Their importance stems from their capacity to offer insightful analysis and produce computations that are applicable to a wide range of disciplines, including statistics, engineering, and physics.

3.5 Model 1: DWT based Historical Image Enhancement Technique using Adaptive Gamma Correction

In Model 1, the CIELAB color space model is used and Discrete wavelet transform is applied up to two levels to obtain approximation and detail coefficient bands. Based on these subbands, gamma correction is applied adaptively to brighten the features of dark and dull images. Here, gamma correction is done on coefficient values instead of intensity values. The coefficient values are enhanced as per the gamma function till a threshold and after that the gamma function behaves linearly. This is done to reduce the possibility of washed-out effect by not enhancing the already bright pixels. The term "washed-out effect" describes an appearance in images that is faded or desaturated and can be observed by lowered contrast, dull colors, and a general lack of illumination. The coefficient values of every image are different so value of threshold will be different for every image. Adaptive gamma correction method is designed to bound the gamma corrected coefficient values within a range so that Inverse DWT results in efficient reconstruction of enhanced image.

3.5.1 Proposed Algorithm for the Model 1

In the first phase of the proposed algorithm, degraded digital image $I(m \times n)$ is taken as an input and it is converted into CIELAB or (L*a*b) color space model. CIELAB color model provides accurate measurement of perceivable colors represented by three color values. Discrete wavelet transform is applied to L channel to get sub-band coefficients. These coefficients are represented by LL, LH, HL and HH, where LL band is called the approximation band and is taken for the next level. DWT uses low pass and high pass filters in horizontal and vertical directions to generate these sub-bands. In the second phase, adaptive gamma correction is applied on the basis of coefficient values. The minimum and maximum values in the sub-band play an important role in adapting the mechanisms of gamma correction. In order to generate the output image as per the spatial domain, Inverse DWT is applied in the reverse order. It is observed that coefficient values require 16-bit format to store the fractional value. The detailed procedure of the first and second phases is explained in Algorithm I and Pictorially demonstrated in Figure 3.8.

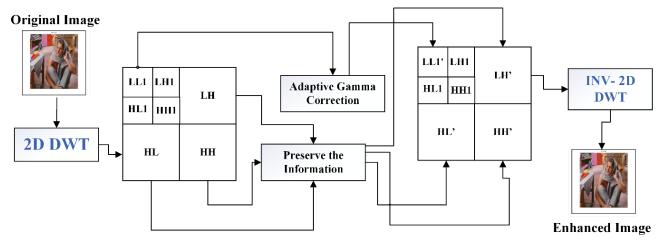


Figure 3.8 An overview of the proposed method.

3.5.2 Phases I: Sub-band Coefficients Generation using DWT

Transform domains are applied to images to analyze the sensitive information within the image. 2D-DWT is applied to the historical images in the proposed algorithm to obtain the approximation and detailed coefficients. The detailed procedure to generate the coefficients is explained in *Algorithm I*.

Pseudo code : Algorithm I

- 1. Input: Input image $I_{m \times n}$
- 2. Output: Sub-band coefficients
- 3. Start
- 4. Read input RGB image $I_{m \times n}$.
- 5. Convert $I_{m \times n}$ to CIELAB color space model L * a * b
- 6. *level* ← 1
- 7. Input= $L_{m \times n}$
- 8. *i* = 0
- 9. While (level < 3)
- 10. Apply DWT to the Input using Eq. (1)
- 11. Generated sub-bands are stored in *LL*[*i*], *LH*[*i*], *HL*[*i*], *HH*[*i*] bands
- 12. **Input** ← *LL*[*i*]
- 13. *level* = *level* + 1
- 14. *i* + +
- 15. While end
- 16. The generated *LL*[1] sub-band is used as input for next phase, which is discussed in Algorithm II.
- 17. end

3.5.3 Phase II: Adaptive Gamma Correction Algorithm

The digital images are captured by camera sensors and the result is completely based on temperature, focal length, aperture, light and size of the camera sensor. Mural images are captured in the low light area, which produces noisy and low-contrast images.

Therefore, an algorithm must be designed such that it can enhance image quality without compromising other details of the image. In the proposed work, we have designed an algorithm to preserve all the details of an image along with the enhancement of contrast. The detailed procedure is illustrated in Algorithm II and graph for proposed adaptive gamma correction is represented by Figure 3.9. In the proposed algorithm, for low intensity values the rate of change of gamma follows an ideal power-law transform function but after a threshold value the rate of change of gamma is linear, it helps to maintain the overall quality of an image and manage to handle the saturation level on the image. Threshold is taken as the average of range of intensity values. This range of intensity values which is different for different images adds to the adaptiveness of gamma correction. Thus, the proposed algorithm is completely different from the traditional way of gamma correction.

The detailed procedure to generate the coefficients is explained in Algorithm II.

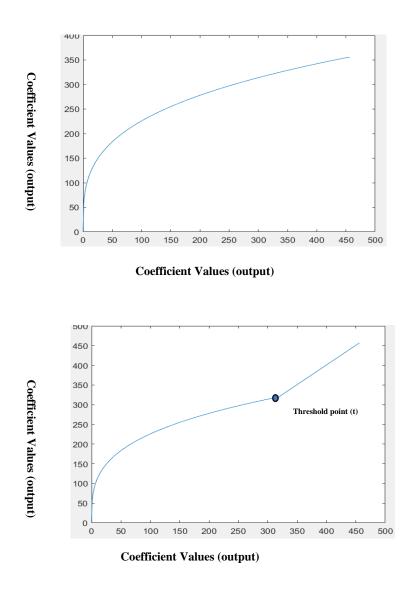


Figure 3.9 : (a) Ideal graph for gamma correction, (b) Graph for proposed adaptive gamma correction.

Pseudocode: Algorithm II

- 1. Start
- 2. Read subband LL[1].
- 3. Calculate *min* and *max* in *LL*1
- 4. c=1;
- 5. r = min: max
- 6. %Adaptative Gamma function start
- 7. $s = c \times r$. ^*gamma*
- 8. s1=s;
- 9. s=(s/max(s)) ×double(max);
- 10. *threshold* = (max + c1)/2
- 11. *for* **I** ←**1** to m
- 12. *for* **j** ←1to **n**
- 13. If LL1(I,j) <threshold
- 14. LL1' = s(LL1)
- 15. else
- 16. *LL*1′ = (*LL*1)
- 17. *If end*
- 18. *for End*
- 19. *for end*
- 20. %Adaptative Gamma function end
- 21. Inverse-2D DWT is used to reconstruct the LL1'
- 22. It is passed further to reconstruct the image *Rec_I* as shown below:
 - a. $Rec_I = IDWT(IDWT(LL'_1, LH_1, HL_1, HH_1)LH^0, HL^0HH^0)$
- 23. Convert *Rec_I* to the color space model.
- 24. End

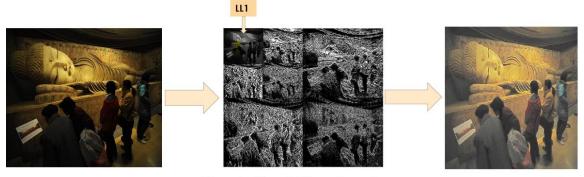
3.5.4 Experimental Results

This section involves an analysis of the proposed algorithm for efficiency and performance. The proposed method for the enhancement of historical images is applied on 64-bit machine architecture with Matlab R2015a software. The test images are selected from several historical images of the online database of Dunhuang and Mogao caves. The input image goes through Algorithm I to generate DWT coefficients and further algorithm II results in the enhancement of low-contrast input image. Fig. 3.10 and Fig. 3.11 displays intermediate results obtained after the proposed method is applied over the test image.

In Fig. 3.10, low contrast input image undergoes Discrete wavelet transformation and results in high contrast output image. In Fig. 3.11, step-by-step results of the proposed method are illustrated. Low contrast input image (Fig. 3.11(a)) is converted to CIE L*a*b color space and undergoes 2-level DWT decomposition (Fig. 3.11(b)). Fig. 3.11(c)) represents the graph of gamma correction function obtained for this test image depending upon minimum and maximum intensity values in LL1 sub-band. Fig. 3.11(d)) is the output image with enhanced contrast.

The proposed algorithm in model 1 is also compared with Visibility Enhancement for Images Captured in Dusty Weather algorithm (VEICDW) [109] and tested on several historical images and comparison of contrast enhancement results followed by their histogram analysis illustrated in Figure 3.12 to Figure 3.17.

A statistical method for seeing and comprehending data distribution is histogram analysis. It entails producing a graphical depiction of how frequently certain values or ranges of values occur within a dataset. Histograms are very helpful for examining the distribution, shape, and central tendency of data. Histogram of original image (Figure 3.12(a)) is right-skewed and distribution curve is inclined towards one side as most of the regions of image are dark. In Figure 3.12(b), the bell-shaped curve indicates that values on which histogram is constructed are normally distributed. This clearly exhibits that image enhanced through proposed method is brighter than the original image. Similarly, histogram of image obtained by applying method [1] (as shown in Figure 3.12(c)) is right-skewed curve.



Input image

Discrete Wavelet Transformation

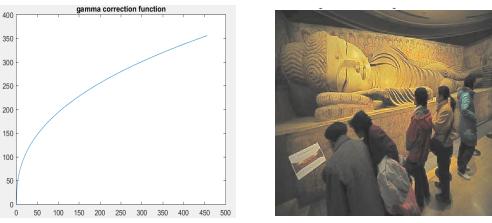
Output image



Figure 3.10 Decomposition of test image into sub-bands using DWT



(b)



(c)

(d)

Figure 3.11 Step-by-step results of the proposed method. (a)Low-contrast image; (b)DWT image after 2level decomposition in CIE L*a*b color space (c)Gamma correction function for L channel (d)Enhanced image.

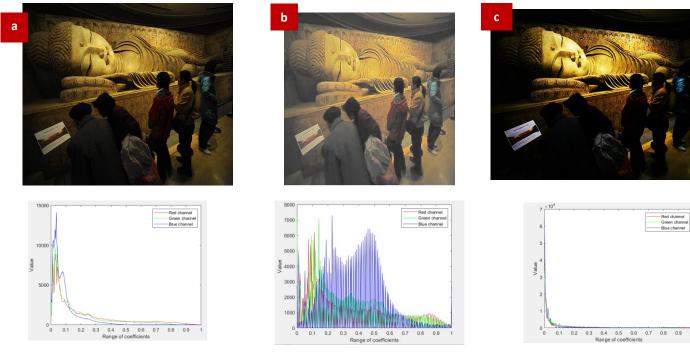
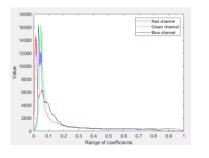
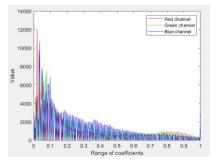


Figure 3.12 Test image 1. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW











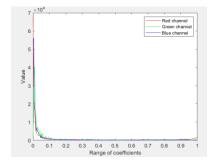


Figure 3.13 Test image 2. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW

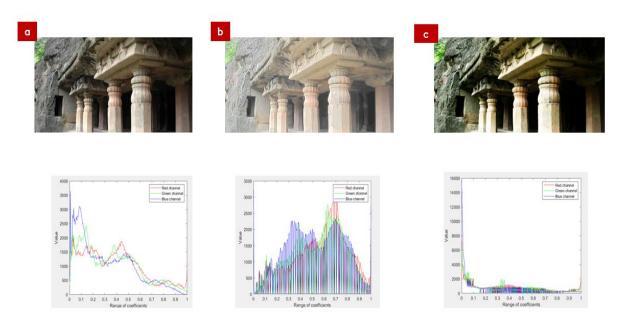


Figure 3.15 Test image 3. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW.

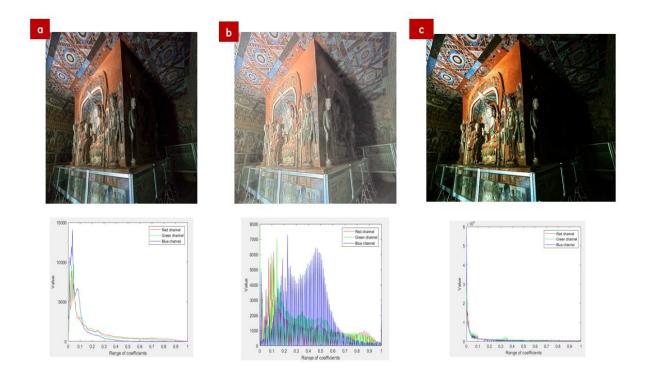


Figure 3.14 Test image 4. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW

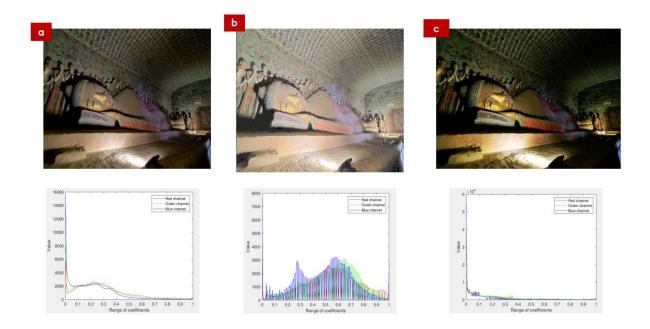


Figure 3.16 Test image 5. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW

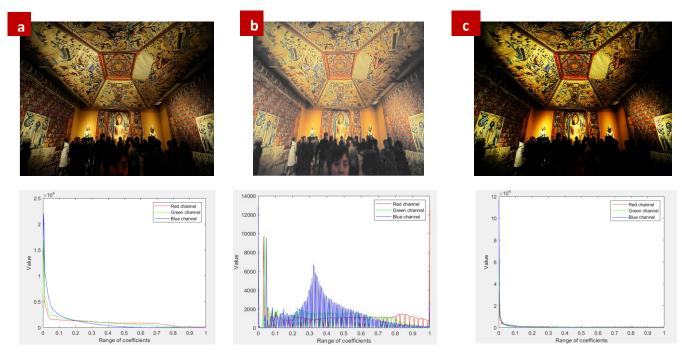


Figure 3.17 Test image 6. Comparison of contrast enhancement results followed by their histogram analysis: (a)original image, (b) proposed method and (c) method in VEICDW.

The results of our proposed algorithm are found impressive and capable to restore deteriorated digital historical images and improve them to obtain the image details more clearly. This method helps to enhance the contrast of an image in to get detailed information of an image more accurately with reduced computational cost. It is also observed that the

restored image may suffer from washed-out effect in which the image appears faded or lacking in contrast causing details to wash out in the brightest areas. It is important to establish empirical measures to prove the efficacy of the proposed algorithm. The measures under observation are Mean square error (MSE), Peak signal to noise ratio (PSNR), Structural similarity index measure (SSIM) and mean for the measure of brightness of the image.

PSNR, MSE and SSIM

PSNR (Peak Signal to noise ratio) usually checks the distortion level of a signal and its quality after retrieval at the receiver's end. In image enhancement, PSNR is calculated between the low contrast original image and its enhanced restored image. Researchers suggest that the higher values of PSNR indicate that a proposed method enhances the contrast of an image and provides more image details. MSE values must be low in order to support efficient image enhancement. MSE and PSNR are inversely proportional to each other, i.e., low MSE indicates higher values of PSNR as shown in Table 3.2. The following equation calculates PSNR (in dB):

$$MSE = \frac{1}{m \times n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [(I(i,j) - I'(i,j))^2]$$
(5)

$$PSNR = 10\log_{10}(\frac{255^2}{MSE})$$
(6)

Where, I(i,j) and I'(i,j) represents the low-contrast image and enhanced image, respectively.

Structural Similarity Index (SSIM) is used to measure the similarity between two digital images, degraded image and restored image; in case of image enhancement. Its values generally lie between 0 to 1, for a perfect match, this value is 1 and 0 when two images are entirely different. The values of MSE, PSNR and SSIM of test images are illustrated in Table 3.2. The value of SSIM shows that the restored image is similar in structure to that of the original image and has additional information of the data content of the image.

Mean value analysis is used to determine the uniform level of intensity values within an image. It represents the amount of brightness of a pixel. Mean value of an improved image is more as compared to mean of low-contrast image. The entropy of an image is a statistical measure of randomness of pixels. A high value of Entropy implies a high amount of information depicted by an image. The proposed method results in an enhanced image with

higher value of entropy and mean as compared to a degraded input image as shown in Table 3.1 and Table 3.2. The proposed algorithm is applied on test images and gives better results as compared to other algorithms which has been validated by using several testcases viz Entropy, Mean, SSIM etc.

| | Entropy | | | Mean | | |
|-------|----------|----------|-----------|----------|----------|-----------|
| Image | Original | Proposed | Method in | Original | Proposed | Method in |
| name | | method | [81] | | method | [81] |
| 1 | 6.654 | 7.0966 | 5.4880 | 0.157 | 0.326 | 0.1198 |
| 2 | 6.766 | 7.0300 | 5.4241 | 0.1899 | 0.363 | 0.1492 |
| 3 | 7.723 | 7.4926 | 7.2807 | 0.342 | 0.531 | 0.3032 |
| 4 | 7.381 | 7.5384 | 6.5033 | 0.245 | 0.444 | 0.1942 |
| 5 | 7.310 | 7.3973 | 6.6807 | 0.253 | 0.469 | 0.1858 |
| 6 | 7.024 | 7.4051 | 5.7657 | 0.211 | 0.400 | 0.1737 |

 Table 3-1 Comparison of experimental values of Entropy and Mean

Table 3-2 Experimental values of MSE, PSNR and SSIM

| Image name | MSE | PSNR | SSIM |
|------------|--------|---------|--------|
| 1 | 0.634 | 60.1105 | 0.5007 |
| 2 | 0.0695 | 59.7078 | 0.4956 |
| 3 | 0.0783 | 59.1905 | 0.6810 |
| 4 | 0.0823 | 58.9758 | 0.5963 |
| 5 | 0.0956 | 58.9758 | 0.6174 |
| 6 | 0.0761 | 59.3146 | 0.5515 |

3.6 Model 2: SWT based Mural Image Enhancement Using Adaptive Fuzzy Gamma Correction

In the previous Model-1, it was observed that there is a possibility of washed-out effect after the process of enhancement on low contrast image. While enhancing the contrast of an image, already bright region of an image become oversaturated and loses the details within an image. The model proposed in this section aims to maintain the contrast range of an image. The proposed algorithm includes two parallel steps of 'contrast correction' and 'color correction' for each image and the last step is to fuse these two images using the weighted average of wavelet coefficients. The proposed model is based on SWT and a fuzzy inference system. In the proposed work, firstly image characteristics are identified using entropy and histogram spread calculation. Then, contrast correction is done by using SWT and an enhanced image is obtained by the combination of these two inputs i.e. color corrected image and contrast corrected image.

A novel algorithm based on the combination of color corrected image and contrast corrected image has been proposed. The proposed algorithm uses fuzzy logic to control the gamma values using a fuzzy system to set its value of dynamically depending upon the image information. It does not require any information other than the image itself. Histogram Spread gives the estimate of spread of histogram over the entire range and its value should be equal to 0.5 for an image with uniform histogram.

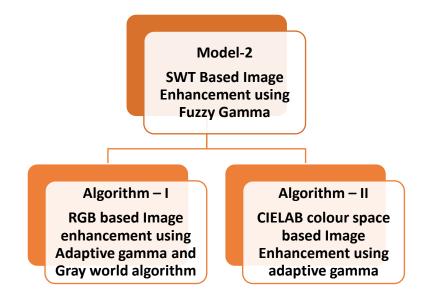


Figure 3.18 Overview of the proposed methodologies for contrast enhancement using SWT and Fuzzy gamma correction.

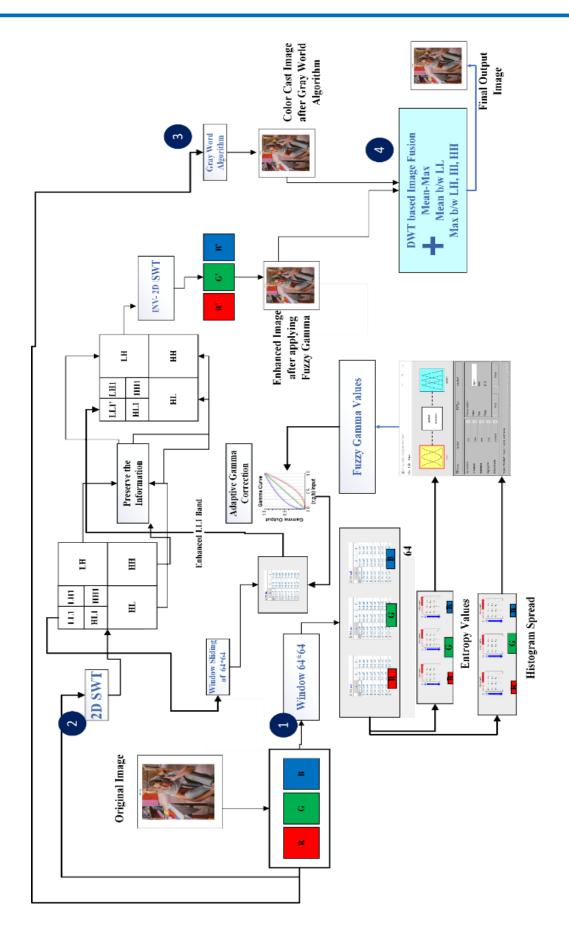


Figure 3.19 Proposed Architecture of the proposed Model 2-Algorithm-I

3.6.1 Algorithm – I RGB based Image Enhancement using Adaptive Gamma and Gray World Algorithm

3.6.1.1 Proposed Algorithm

The proposed algorithm for contrast enhancement of degraded historical images uses Stationary wavelet transform to obtain coefficient values, entropy and histogram spread to obtain image characteristics, a fuzzy system to achieve adaptive gamma correction, gray world algorithm is applied to get color corrected image and finally inverse SWT is done to obtain enhanced image. The advantage of SWT over DWT is that, in SWT the number of coefficients generated is same as the size of image. This helps to maintain the quality of image. The proposed algorithm is divided into four modules.

3.6.1.1.1 Module 1: Fuzzy Gamma

- 1. Read a color Image of size $m \times n$
- 2. Resize into 512×512 and obtain its R, G, B channels
- 3. Consider a window of size 64×64 which slides over the image to calculate entropy and histogram spread of each window or cell array
- 4. Mamdani Fuzzy Inference System is designed where entropy and histogram spread are two crisp inputs. Based on this entropy and histogram spread obtained for every window, fuzzy rules are applied and defuzzification is performed.
- 5. Fuzzy Rule Formation
 - If (entropy is high) and (histogram spread is high) then (gamma is high)
 - If (entropy is low) and (histogram spread is low) then (gamma is low)
- 6. Defuzzification method 'centroid' is used to convert fuzzy value of gamma to a crisp value which is further used for gamma correction. The value for gamma is the output of module 1.

3.6.1.1.2 Module 2: SWT and Gamma Correction on Coefficient Values

- 1. For each R, G and B channel of input image, a 2-D SWT is applied on individual channel and all sub-bands are preserved.
- 2. Here gamma correction is done on LL1 band or approximation coefficients instead of intensity values. This LL1 band is divided into windows of size 64X64 and for every

window a different value of gamma is provided by FIS to perform gamma correction and obtain new LL1 band.

- 3. Merge new LL1 band with other sub-bands and apply 2-D inverse SWT. Inverse SWT is used to reconstruct the R', G' and B' channels.
- 4. The resultant R', G' and B' channels are then combined to get an enhanced image.

3.6.1.1.3 Module 3: Gray World Algorithm

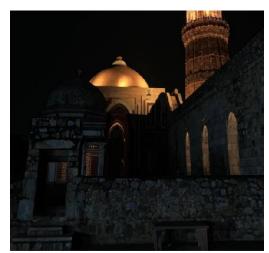
- Due to the fact that the color of the same objects may and often does look different under different lighting conditions, some of these conditions have been standardized so printed color work can be assessed predictably, and digital images serving as a cast as blue like other conventional histogram-based techniques.
- 2. Color cast detection and correction is performed using gray world algorithm which requires non-linearity factors dependent on the type of media.
- 3. This scaling value is used to scale the entire image linearly
- 4. In practice the average of each individual channel is used to calculate a separate scaling value for each channel.
- 5. This way the illumination on the different channel is eliminated independent.

3.6.1.1.4 Module 4

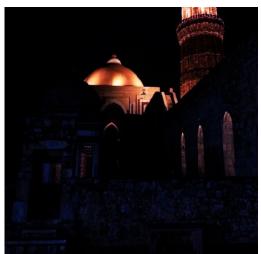
- 1. Output results of fuzzy gamma system and gray world algorithms are passed to DWT.
- 2. Through experimental results it has been found that the Mean of Approximation coefficients give better results.
- 3. Maximum of other coefficient bands between coefficient values are taken.
- 4. In last, Inverse DWT is performed to get the final result.
- 5. Mean of approximation coefficients and max values among detailed coefficients are taken of the module 2 and module 3 generated image. The final image is produced after applying the inverse DWT.

3.6.1.2 Experimental Results

This section involves an analysis of the proposed algorithm for efficiency and performance. The proposed method for enhancement of historical images is applied on 64-bit machine architecture with MATLAB R2015a software. The test images are selected from several historical images of the online database of Dunhuang and Mogao caves. The input image goes through phase 1 to generate DWT coefficients and further phase 2 results in the enhancement of low-contrast input image. Fig. 3.20 displays intermediate results obtained after the proposed method is applied to the test images. Here, Fig. 3.20 (a) is the original input image with poor contrast.



(a) Original image



(b) Image Intensification (VEICDW)



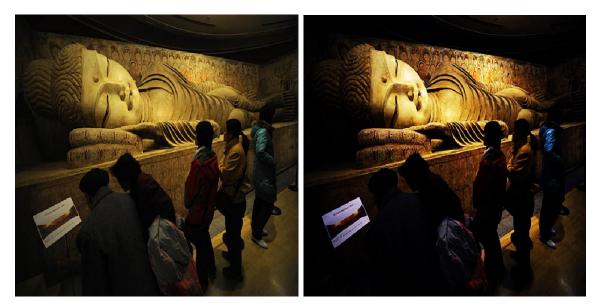
(c) Histogram Equalization



(d) Output of proposed algorithm

Figure 3.20 Test Image 1: comparison of different enhancement techniques

Fig 3.20 (b) is the result of image intensification method in which image features of the darker regions are suppressed and features in bright region sharpens up leading to loss in certain features of the input image. Using the histogram equalization method to enhance the contrast of the input image may result in nicely enhanced image but it also suffers from the problem of over saturation of bright regions which leads to loss of image quality and naturalness as shown in Fig 3.20 (c). The restored image through the proposed algorithm as shown in Fig 3.20 (d) appears to be more natural and realistic due to evenly enhanced image.

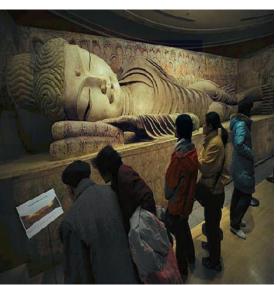


(a) Original image

(b) Image Intensification (VEICDW)



(c) Histogram Equalization



(d) Output of proposed algorithm

Figure 3.21 Test image 2: comparison of different enhancement techniques



(a) Original image

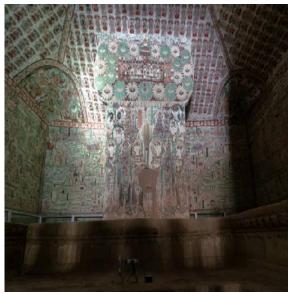
(b) Image intensification



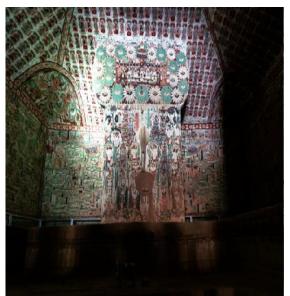
(c) Histogram equalization

(d) Output of proposed algorithm

Figure 3.22 Test image 3: comparison of different enhancement techniques



(a) Original image



(b) Image Intensification





(c) Histogram Equalization

(d) Output of proposed algorithm

Figure 3.23 Test image 4: comparison of different enhancement techniques

3.6.1.2.1 Histogram Spread Analysis

The primary objective of histogram spread is achieving a balanced and evenly distributed representation of pixel intensities in an image. A well-spread histogram makes the most use of the dynamic range by spanning a wider variety of intensity values. The uniform contrast is achieved, when Histogram spread, value is approaching to 0.5 and when it is exceeding the limit of 0.5, image is over-saturated and details are lost. This may improve the image's overall visual quality by improving contrast and detail visibility.

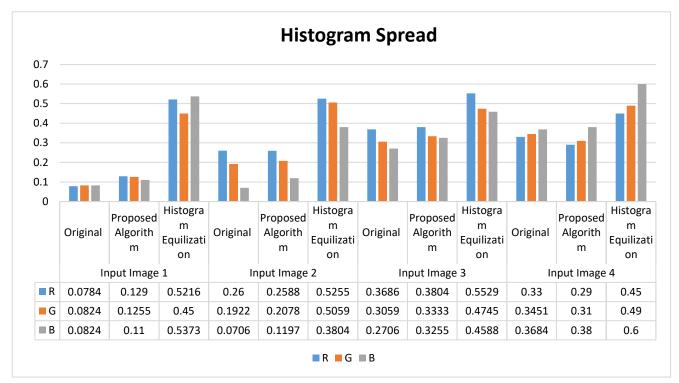
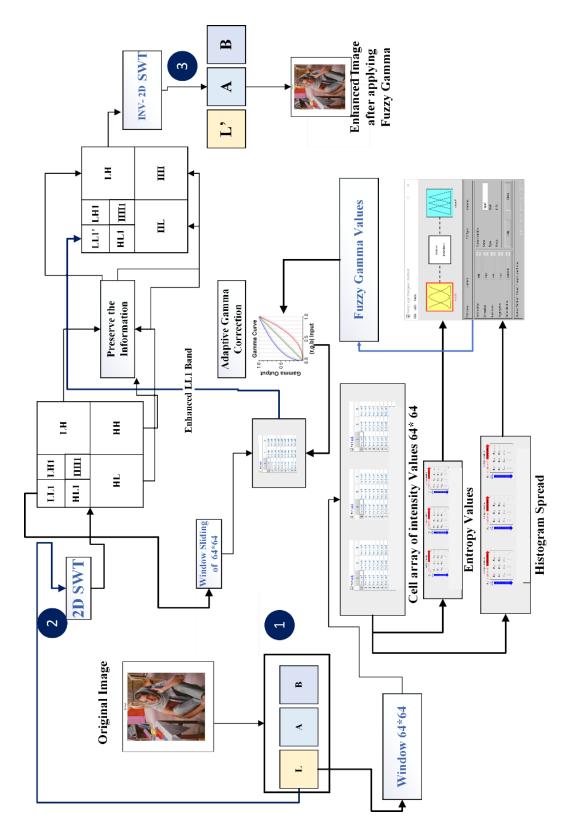


Figure 3.24 Histogram Spread Analysis



3.6.2 Algorithm – II CIELAB color space-based Image Enhancement using adaptive gamma

3.6.2.1 Proposed algorithm

The algorithm discussed in section 3.6 for contrast enhancement of degraded historical images uses discrete wavelet transform to decompose the image in set of coefficient values, then adaptive gamma correction is done to obtain an enhanced image. The rate of change of gamma depends on the intensity values of the image. Though the method works well for low contrast regions but somehow a washed-out effect is observed. This problem is further addressed in section 3.7 and algorithm-I is proposed where a fuzzy gamma value is used adaptively on the image by dividing it into chunks of size 64×64. Entropy and histogram spread is used to obtain image characteristics, a fuzzy system to achieve adaptive gamma correction, gray world algorithm is applied to get color corrected image and finally inverse SWT is done to obtain enhanced image. It is observed from the results of algorithm I that it might suffer from the problem of patchy image due to abrupt change in gamma value obtained by fuzzy inference system. To overcome this problem of patches, another algorithm-II is proposed which processes the degraded image in CIE L*a*b color space. The proposed algorithm is divided into three modules.

3.6.2.1.1 Module 1: Fuzzy Gamma

- 1. Read a color Image of size m x n and convert into CIE L*a*b color space.
- 2. Resize into 512×512 and obtain its L, a and b channels
- Consider a window of size 64×64 which slides over the L channel of the image to calculate entropy and histogram spread of each window or cell array
- 4. A Mamdani fuzzy inference system is designed where entropy and histogram spread are two crisp inputs. Based on this entropy and histogram spread obtained for every 64×64 window, fuzzy rules are applied and defuzzification is performed.
- 5. Rule Formation
 - *if(entropy is high) and (histogram spread is high) then (gamma is high)*
 - *if(entropy is low) and (histogram spread is low) then (gamma is low)*
- 6. The defuzzification method 'centroid' is used to convert fuzzy value of gamma to a crisp value which is further used for gamma correction. The value for gamma is the output of module 1.

3.6.2.1.2 Module 2: SWT and Gamma Correction on coefficient values

- 1. A 2-D SWT is applied on L channel and all sub-bands are preserved.
- Here gamma correction is done on LL1 band or approximation coefficients instead of intensity values. This LL1 band is divided into windows of size 64×64 and for every window a different value of gamma is provided by FIS to perform gamma correction and obtain new LL1 band.

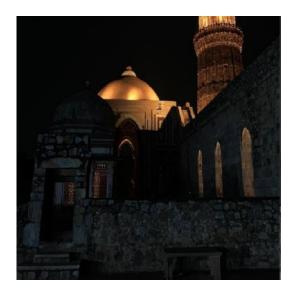
3.6.2.1.3 Module 3: Inverse SWT

- 1. Merge new LL1 band with other sub-bands and apply 2-D inverse SWT. Inverse SWT is used to reconstruct the image which is in CIE L*a*b color format.
- 2. This image is now converted back into RGB form which is actually an enhanced image having uniform contrast.

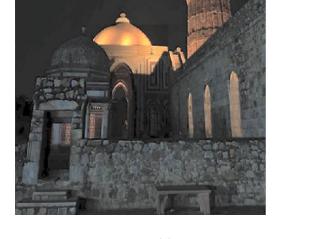
3.6.2.2 Experimental results

This section examines the performance and efficiency of the suggested algorithm. The suggested technique for improving historical images is implemented using Matlab R2015a on a 64-bit system architecture. The test images were chosen from the online archive of historical photos of the Mogao and Dunhuang caves. The input image is processed by Algorithm II to provide SWT coefficients, and a fuzzy inference system provides an adjustable gamma value to further improve the low-contrast input image. After applying the suggested procedure to the test images, the intermediate results are shown in Figures 3.25 to 3.28.

The original input test images have poor contrast. Some regions are dark and some regions are bright. The output of algorithm I gives an enhanced image where contrast enhancement is done adaptively in blocks of 64×64 but it suffers from the problem of uneven contrast enhancement which sometimes looks like a patchy image. The same test image when undergoes algorithm II produces a bright image with seamless or even contrast enhancement. The structural details are preserved and no washed-out effect is observed.







(b)

(c)

Figure 3.25 Test image 1. (a) Original image (b) result after Algorithm-I and (c) result after Algorithm-II





(b)

(c)

Figure 3.26 Test image 2. (a) Original image (b) result after Algorithm-I and (c) result after Algorithm-II





(b)



(c)

Figure 3.27 Test image 3. (a) Original image (b) result after Algorithm-I and (c) result after Algorithm-II





(b)



(c)

Figure 3.28 Test image 4. (a) Original image (b) result after Algorithm-I and (c) result after Algorithm-II

| | Original | Algorithm-I | Algorithm-II | Histogram Equalization Algorithm |
|---------------|----------|-------------|--------------|--|
| Input Image-1 | 5.58 | 6.46 | 6.70 | 5.10 |
| Input Image-2 | 6.65 | 7.17 | 7.3 | 5.64 |
| Input Image-3 | 7.14 | 7.62 | 7.80 | 5.73 |
| Input Image-4 | 7.53 | 7.50 | 7.60 | 5.69 |

Table 3-3 Comparison of entropy values of different contrast enhancement methods

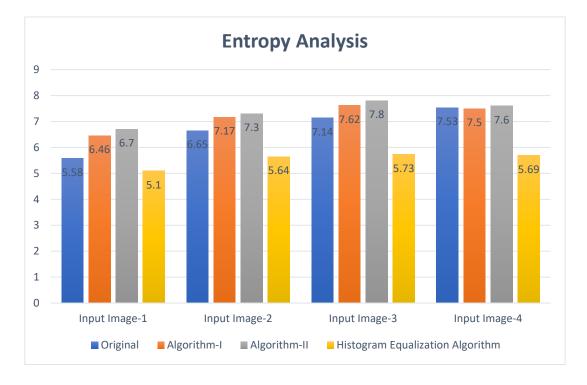


Figure 3.29. Pictorial representation of comparison between Entropy analysis of different contrast enhancement methods

3.7 Discussion

Values of entropy and mean of enhanced image when compared to that of the degraded image clearly indicate that the proposed method results in bright image with maximum structural details. Table 3.3 represents the comparison of entropy values of different contrast enhancement methods which is further represented pictorially by Figure 3.29. The future work can be extended to other color models using other transforms. The proposed algorithm is based on simple mathematical calculations; therefore, the method can be implemented in real-time applications such as Internet of things-based image acquisition applications. It is evident that proposed algorithm retains the structural properties of the images after improving the contrast of image due to adaptive feature of gamma correction along with DWT. Adaptive gamma correction also prevents the resultant image to get washed out in high intensity regions.

3.8 Conclusion

To evaluate the performance of the proposed methods PSNR, MSE and SSIM are evaluated. The proposed algorithms in Model 1 and Model 2 are applied to several historical images. It is evident from visual analysis of output image that the low contrast input image with dark regions is enhanced to an extend that the output or the restored image displays all of the regions clearly. It is clear that wavelet transform is a signal processing technique which can display the signals on in both time and frequency domain. Wavelet transform is superior approach to other time-frequency analysis tools because its time scale width of the window can be stretched to match the original signal, especially in image processing studies.

Chapter 4

MSB BASED CELLULAR AUTOMATA FOR EDGE DETECTION

4.1 Introduction

In the previous chapter, discussions were confined to algorithms based upon the contrast enhancement, where we have discussed transform-based contrast enhancement techniques. This chapter address objective 2, and the proposed algorithm is designed on the principle of cellular automata. Edge Detection is a vital pre-processing phase in image processing and computer vision which detects boundaries of foreground and background objects in an image. Difference between significant and spurious edges plays an important role in the accuracy of edge detection. Spurious edges are weak or not so important edges in the image while significant images are strong edges which define the objects in an image. This chapter introduces a new approach for edge detection in images based on cellular computing. Digital images contain a significant amount of information; therefore, edge detection should be fast and processed in minimum time without facing any complexity in a shared network environment.

Edge detection is a procedure to detect contour of objects by finding the discontinuities or change in brightness within an image. Edge detection is an important step in digital image processing and computer vision by preserving the important structural properties in an image. There are several edge detection techniques [9, 32, 65, 110, 111] and can be broadly grouped into two categories. The gradient-based method detects the edges by computing the maximum and the minimum in the first derivative of an image. In the Laplacian method,

edges are traced by locating zero crossings in the second derivative of the image. There are problems of false edge detection and missing true edges which can significantly affect the result of object recognition, pattern recognition and feature extraction processes.

Existing edge detection methods are complex to implement and fail to produce satisfactory results in the case of noisy images. Some methods tend to give spurious edges and some tend to miss true edges in the image. The purpose of using cellular computing approach is to reduce complexity and processing time as the method is computationally simple and fast due to parallel processing. The results of Mendeley Dataset images are compared with the results of existing edge detection techniques by evaluating MSE and PSNR values which indicates the promising performance of the proposed algorithm. Visually, the proposed method tends to produce better results which discriminate objects and interpret the edges more clearly even for cluttered and complex images.

4.2 Concept of Cellular Automata

Cellular Automata (CA) find its wide applications in the area of Image processing and computer vision [7]. Theory of self-reproducing Automata was initiated by J. Von Neumann [112, 113] in 1950's. Stephen Wolfram extended the concept of automata by developing CA Theory [114-116]. A digital image is represented by a 2-D array for a grayscale image and a collection of three 2-D arrays for color image. Two dimensional Cellular Automata can be implemented on an image with an ease [117]. Various possible applications of CA in image processing ranges from edge detection algorithms, translation of images, rotation through an angle, scaling operations like thinning and zooming, finding contour and edges for image segmentation and other NP-complete problems, such as graph coloring or satisfiability, designing a controlled random number generator with smaller aliasing rate than a linear counter based on shift register and XOR gates and pattern generation [118].

4.2.1 Structure of Cellular Automata

Cellular Automata is a finite state machine having multiple cells. Cellular automata is categorized into two category: 1) 1-D cellular automata 2) 2-D Cellular automata.

One-dimensional CA is a linear array of cells and a two-dimensional CA [117, 119, 120] is a grid of cells where each cell is influenced by its neighboring cells. There is a finite range of possible states of a cell. State of a cell is updated simultaneously depending upon previous

states of its neighboring cells. Some of the salient features of cellular Automata are listed below:

- A Cellular Automaton is a finite, regular lattice of simple finite state machines that change their states synchronously, according to a local update rule that specifies the current state of each cell based on the previous state of its neighbours.
- Cellular automata are a collection of cells that each adapts one of a finite number of states. Single cells change in states by following a local rule that depends on the environment of the cell.
- A cellular automaton is a discrete model studied in computer science, mathematics, physics, complexity science, theoretical biology and microstructure modeling.
- CA are both inherently parallel and computationally simple. This means that it can be implemented efficiently in hardware using just logic gates.

Cellular Automata can be represented as (D, S, N, f, B); where, D defines the dimension of CA i.e. 1D, 2D and so on, S holds set of possible states of all cells in a CA generally (0,1), N defines the set of neighborhood states like Von-neumann or Moore or Extended Moore neighborhood as shown in Figure 4.1, f is transition function depicted by Transition rule and B defines the boundary condition like fixed boundary condition, periodic boundary condition, adiabatic boundary condition or reflexive boundary condition as shown in Figure 4.2.

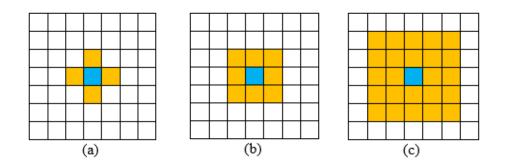


Figure 4.1 Number of neighborhood states. (a)Von-neumann, (b) Moore, (c) Extended Moore neighborhood

There are two popular neighborhood structures in Cellular Automata: Von-neumann and Moore. Von-neumann neighborhood has four neighbors surrounding a cell and in Moore neighborhood, there are eight neighbors. The radius of neighborhood is 1. In extended Moore neighborhood, radius is increased to 2 having 24 neighbors and one center cell [120, 121]

Nine-neighborhood cells with radius one and every cell having two states are also known as 2D Cellular automata, and in each iteration, a cell has two possible values, either 0 or 1, and accordingly, distinct neighborhood configurations will be 512

In equation (1), Let t, i represent time and index of a cell, respectively. New state of a cell $(x_{i,i}^{t+1})$ depends upon the current state of its neighboring cells.

$$x_{i,j}^{t+1} = f(x_{i-1,j-1}^t, x_{i-1,j}^t, x_{i-1,j+1}^t, x_{i,j-1}^t, x_{i,j}^t, x_{i,j+1}^t, x_{i+1,j-1}^t, x_{i+1,j}^t, x_{i+1,j+1}^t)$$
(1)

Since f() is a Boolean function of combinational logic, it produces a binary value depending upon the local rule of elementary cellular automata. Therefore, $x_i^{t+1} \in (0,1)$. At every discrete time step (clock cycle), Boolean cellular automata sites update their state by using some rules (combination function or rule).

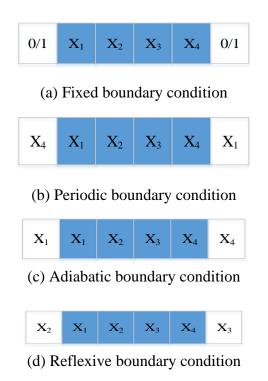


Figure 4.2 Cellular Automata boundary conditions

4.2.2 Rule Formation

Elementary CA has two states, 0 and 1, for every cell. For a combination of three neighbors there can be $8(=2^3)$ possible combinations i.e. 000,001,...,111. There are total of 2^8 rules, each rule is represented by an 8-bit binary number i.e. Rule 0 to Rule 255. For a two state nine neighborhood CA, there exist 2^{2° possible rules. Among these, 2^9 rules are linear and

can be determined by Figure 4.3. Remaining $2^{2^9} - 29 (= 502)$ are non-linear rules [120, 122, 123].

| 64 | 128 | 256 |
|----|-----|-----|
| 32 | 1 | 2 |
| 16 | 8 | 4 |

Figure 4.3 Dimensional CA rule convention

Cellular automata have several advantages over other methods of computation. Simplicity of implementation makes it appropriate for solving a complex problem in less computational time complexity. CA is comparatively faster than other methods [124, 125].

4.3 Related Work

According to literature so far, CA roots itself for more than two decades in image processing [126]. In [120], Choudhury et al. applied eight basic 2-Dimensional Cellular Automata rules (Rule 2, 4, 8, 16, 32, 64, 128 and 256) to an image for its translation in all directions. Various rules are applied to obtain various operations on images like scaling and thinning horizontally as well as vertically, and zooming of symmetric images. Qadir et al. [127] extended the concept of translation of the image by using twenty-five neighborhoods instead of nine neighborhoods. This method for translation was used in gaming applications. In [128], Khan et al. proposed that hybrid CA is the possible solution for rotation of images through an arbitrary angle. According to him, 2-D CA rules are applied to rotate an image by an angle π about x and y axis respectively.

Determination of rule set is a crucial step in CA. Specifying and selecting rules manually is a slow and laborious process, also, it may not scale well to larger problems. The Fuzzy Cellular Automata is employed with fuzzy logic, having fuzzy states of a cell and fuzzy functions for transition rules. Fuzzy CA (FCA) is a special class of CA which is employed to design the

pattern classifier [129]. Wang Hong et al. [130] suggested a novel method for image segmentation based on fuzzy cellular automata. In [131], Moore and Patel used the property of Cellular Learning Automata to enhance the edges detected by fuzzy logic. In [110], Nayak et.al. compared the performance of existing edge detection techniques with their proposed method based on extended neighborhood CA and null boundary conditions.

4.4 Proposed Methodology

Existing edge detection methods are complex to implement and fail to produce satisfactory results in the case of noisy images. Some methods tend to give spurious edges and some tend to miss true edges in the image. The purpose of using cellular computing approach is to reduce complexity and processing time as the method is computationally simple and fast due to parallel processing. Block diagram of the proposed algorithm is represented by Fig 4.4.

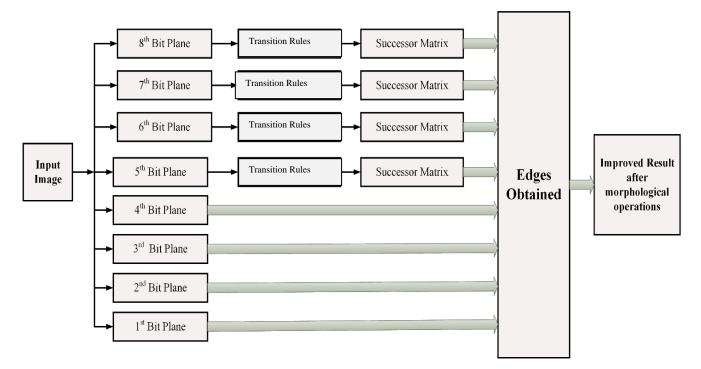


Figure 4.4 Flowchart of proposed method

In the proposed algorithm, all input images are grayscale. This method highlights the contribution made to the overall appearance of an image by significant bits. Considering the fact that each pixel is represented by 8 bits. Higher-order bits i.e. first four most significant bits of binary representation of intensity depicts maximum image information. Contour of an image of the region within an image (as shown in Fig. 4.5) is identified by the proposed algorithm in section 4.4.2.

4.4.1 Proposed Algorithm

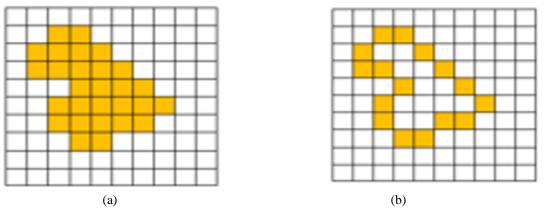


Figure 4.5 Illustration (a) region in an image (b) Contour identified by applying these four rules.

The image is first divided into its bit planes which is called bit plane slicing, then these transition rules are applied parallelly to every binary bit plane. Following are the steps for edge detection method based on cellular automata:

- 1. Each cell represents an image pixel with certain intensity or pixel value.
- 2. Bit-plane slicing. Each pixel is represented by 8 bits. Higher-order bits i.e., first four most significant bits of binary representation of intensity depict maximum image information.
- 3. According to Moore neighborhood, four linear rules are identified which can efficiently result in identification of boundary of a region.

Formation of transition rule

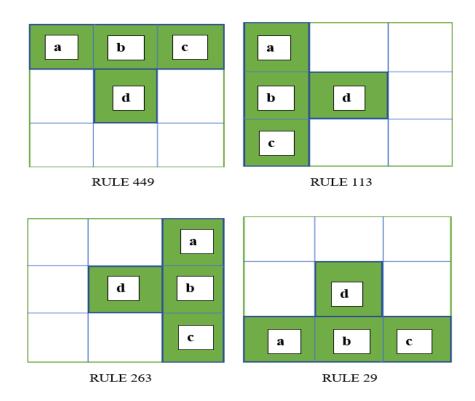


Figure 4.6 Conceptual representation for identification of transition rules of proposed algorithm The state of a cell in the next generation is determined by the previous state of its neighboring cells and all cells are updated synchronously resulting in unit time complexity. Every cell can have two states, 0 or 1. In a 1x3 neighborhood structure, state of d pixel is updated by considering previous states of pixel a, b and c. Figure 4.6 illustrates the method to apply identified composite rules by taking different set of 1x3 neighbors to update value of pixel d.

These four rules can be represented as four borders which result in edge detection when applied by sliding a window of 3x3 pixels over an image of size *mxn*. Four composite rules for edge detection are computed as follow:

- a. Rule 29 = Rule 16 \oplus Rule 8 \oplus Rule 4 \oplus Rule 1
- b. Rule 113 = Rule 64 \oplus Rule 32 \oplus Rule 16 \oplus Rule 1
- c. $Rule 263 = Rule 256 \oplus Rule 4 \oplus Rule 2 \oplus Rule 1$
- d. Rule 449 = Rule 256 \oplus Rule 128 \oplus Rule 64 \oplus Rule 1
- Integration of successor matrices results in edges present in the image. *Rule*29 || *Rule*113 || *Rule*263 || *Rule*449
- 5. The resultant successor matrix bit planes are merged into a gray image.

- 6. Binarization of the image is done on the basis of Otsu's threshold technique.
- 7. Some morphological operations are performed to enhance the results by removing noise and obtain true edges in the given input image as illustrated in Fig 4.5.

Pseudo Code: Automata Based Edge Detection

Input: Input image $Img_{(m \times n)}$ Output: Edges present in image

- 1. Start
- 2. Read input RGB image $Img_{(m \times n)}$
- 3. Convert $Img_{(m \times n)}$ to gray *image I*
- 4. Perform bit plane slicing and obtain 8 different matrix.
 - for i = 1:8

$$Ai = bitget(i, i)$$

end for

5. for matrices corresponding to first 4 MSBs repeat step 6 to step

| 6. for $i = 2: m - 1$ |
|--|
| for $j = 2: n - 1$ |
| 7. If $A(i,j) = 1$ |
| 8. $If (A(i,j-1)\&\&A(i-1,j-1)\&\&A(i+1,j-1)) $ |
| (A(i-1,j-1)&&A(i-1,j)&&A(i-1,j+1)) |
| (A(i+1,j-1)&&A(i+1,j)&&A(i+1,j+1)) |
| (A(i-1,j+1)&&A(i,j+1)&&A(i+1,j+1))) = 1 |
| 9. then $A'(i, j) = 0$ |
| 10. end if |
| 11. else $A'(i, j) = 1$ |
| 12. end if |
| 13. end for |
| 14. end for |
| 15. $finalimage_4bits = A'8 * 2^7 + A'7 * 2^6 + A'6 * 2^5 + A'5 * 2^4 + A4 * 2^3 + A3 * A3 * A'5 + A'$ |
| $2^{2} + A2 * 2^{1} + A1 * 2^{0}$ |
| 16. End |
| 17 Denform morphological exercises to nomeno poice and obtain two odges in given image |

17. Perform morphological operations to remove noise and obtain true edges in given image.

4.5 Experimental Results

The MATLAB R2015a software has been used to implement the proposed algorithm. In this chapter, a comparison of proposed method is carried out against the commonly deployed Gradient and Laplacian based Edge Detection techniques. These techniques suffer the problems of inaccurate edge detection, missing true edges, producing thin or thick lines and extra edges due to noise etc.

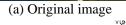
The results of Berkeley dataset [132] are used to test the algorithm and results are illustrated in Figure 4.7 and Figure 4.8. The results of the proposed algorithm are compared with existing edge detection techniques and indicate promising performance of the proposed algorithm by evaluating MSE and PSNR values as given by Table 4-1 Comparison of MSE and PSNR values of test images. [12, 64, 65, 133]. Images from Berkeley dataset are used for evaluation of the proposed method because ground truths are also available in this dataset. Further, the implementation of algorithm is extended to degraded mural images. The mural images are tested by the proposed algorithm and the results are illustrated in Figure 4.9 Figure 4.10

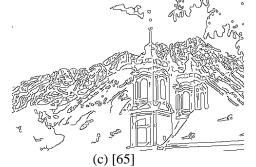
Figure 4.11 Figure 4.12. Promising results thus obtained implies the effectiveness of the proposed algorithm. Evaluation of test images show that proposed method exhibits better performance even for noisy and cluttered images. Visually, the proposed method produced promising results of edge detection when compared to canny, sobel and prewitt edge detectors. Canny consists of several spurious edges whereas sobel and prewitt lack some of the strong edges. The results of Mendeley Dataset [134] are shown in Table 4-2 and Figure 4.13, Mean square error (MSE) and Peak signal to noise ratio (PSNR) is used to compare the quality of reconstructed image with its ground truth image. If an operator gives a resultant image with less PSNR and high MSE then operator has high MSE which indicates that the operator has high edge detection capability.

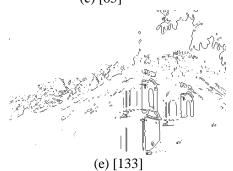
| | Metric | Method in [65] | Method in [64] | Method in [133] | Method in [12] | MSBCA (proposed method) |
|--------------|-------------|-------------------|-------------------|--------------------|-------------------|-------------------------------|
| Test Image 1 | MSE PSNR | 0.1385 56.7504 | 0.0893 58.6550 | 0.0890 58.6699 | 6.1127 15.5947 | 0.0788 59.6402 |
| Test Image 2 | MSE PSNR | 0.2114 54.9143 | 0.2002 | 0.2002 | 4.1324 15.5947 | 0.2102 |

Table 4-1 Comparison of MSE and PSNR values of test images.



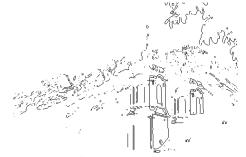




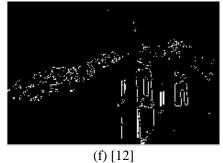




(b) Ground truth



(d)[64]





(g) Proposed MSBCA method

Figure 4.7 Test image 1: Comparison of edge detection results: (a) Original Image (b) Ground truth (c) Method in [65] (d) Method in [64] (e) Method in[133] (f) Method in [12] (e) Proposed method MSBCA

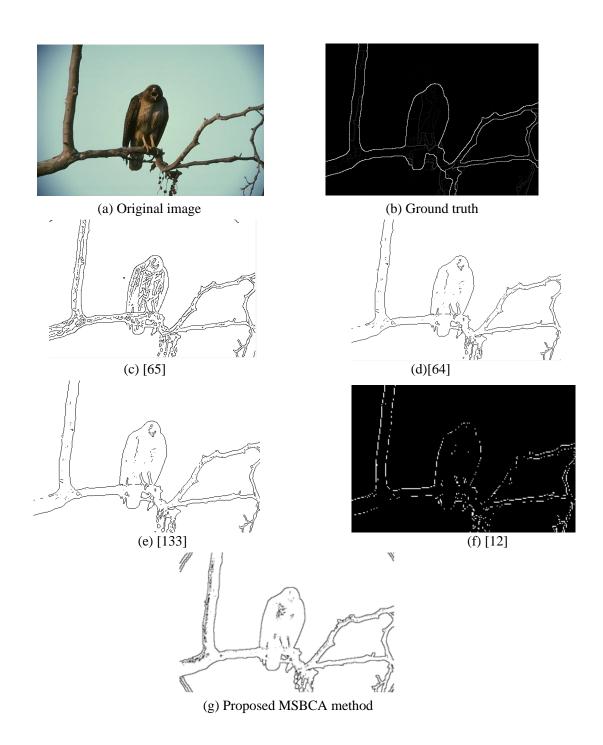


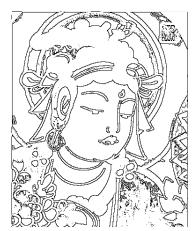
Figure 4.8 Test Image 2.: Comparison of edge detection results: (a) Original Image (b) Ground truth (c) Method in [65] (d) Method in [64] (e) Method in [133] (f) Method in [12] (e) Proposed method MSBCA



(a)original image



(c) [65]



(b) proposed method MSBCA



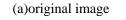
(d)[64]

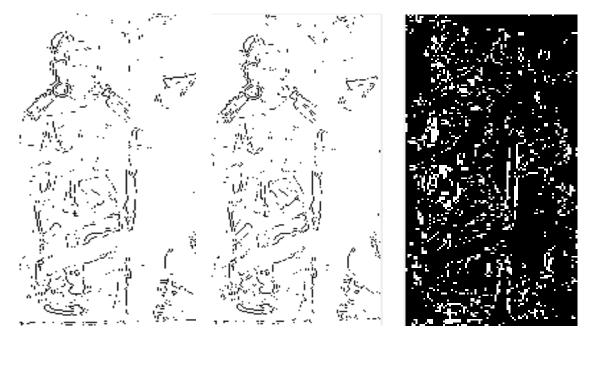


Figure 4.9 Comparison of edge detection results: (a)original image(b) proposed method MSBCA (c)method in [65] (d)method in [64] (e)method in [133] (f) method in [12]



(b) proposed method MSBCA (c) [65]





(d)[64]

(e)[133]

(f) [12]

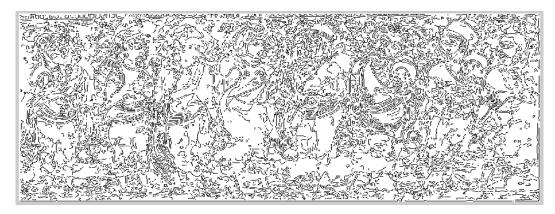
Figure 4.10 Comparison of edge detection results: (a)original image (b) proposed method MSBCA (c)method in [65] (d)method in [64] (e)method in [133] (f) method in [12]



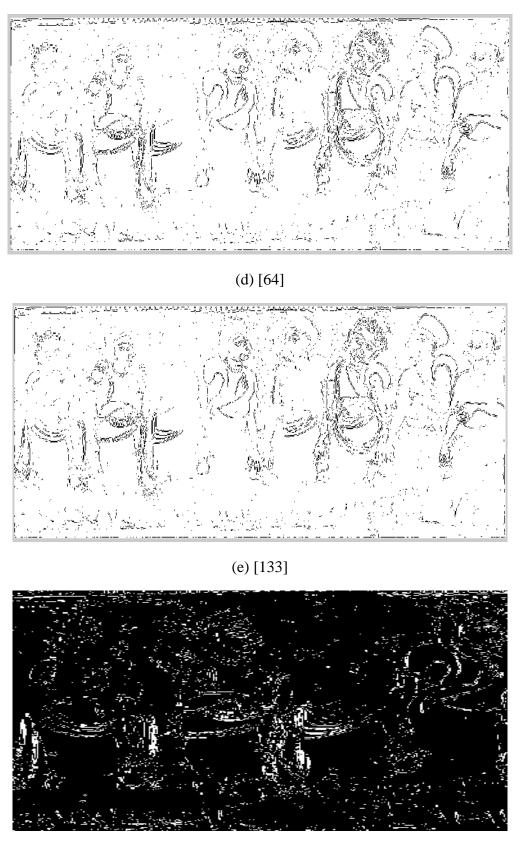
(a) original image



(b) Proposed method MSBCA

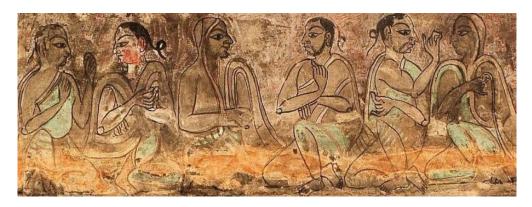


(c) Method in [65]

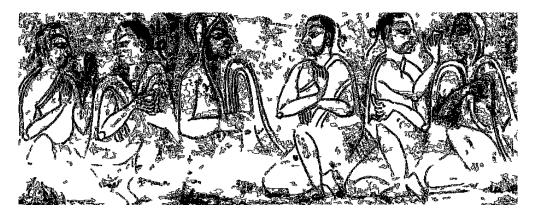


(f) [12]

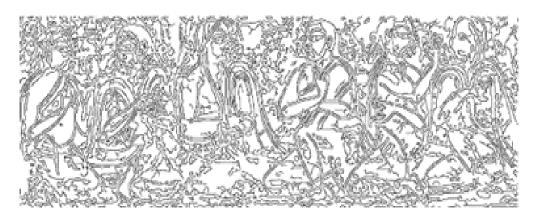
Figure 4.11: Comparison of edge detection results: (a)original image (b) proposed method MSBCA (c)method in [65] (d)method in[64] (e)method in[133] (f) method in[12]



(a)original image



(b) proposed method MSBCA



(c) **[65]**



(d) [64]



(e) [133]



(f) [12]

Figure 4.12 Comparison of edge detection results: (a)original image (b) proposed method MSBCA (c)method in [65] (d)method in [64] (e)method in [133] (f) method in [12]

| Original image | | Method in | Method in [64] | Method in | Proposed |
|----------------|------|-----------|----------------|-----------|----------|
| | | [65] | | [133] | method |
| Image 1 | MSE | 0.9172 | 0.9741 | 0.9745 | 0.8810 |
| | PSNR | 0.3754 | 0.1138 | 0.1122 | 0.5500 |
| Image 2 | MSE | 0.9201 | 0.9720 | 0.9718 | 0.9156 |
| | PSNR | 0.3616 | 0.1232 | 0.1242 | 0.3831 |
| Image 3 | MSE | 0.9258 | 0.9740 | 0.9741 | 0.8855 |
| | PSNR | 0.3346 | 0.1146 | 0.1142 | 0.5283 |
| Image 4 | MSE | 0.9046 | 0.9586 | 0.9585 | 0.8738 |
| | PSNR | 0.4355 | 0.1837 | 0.1840 | 0.5858 |
| Image 5 | MSE | 0.9313 | 0.9671 | 0.9670 | 0.8825 |
| | PSNR | 0.3092 | 0.1453 | 0.1459 | 0.5427 |

 Table 4-2 Experimental results for test images

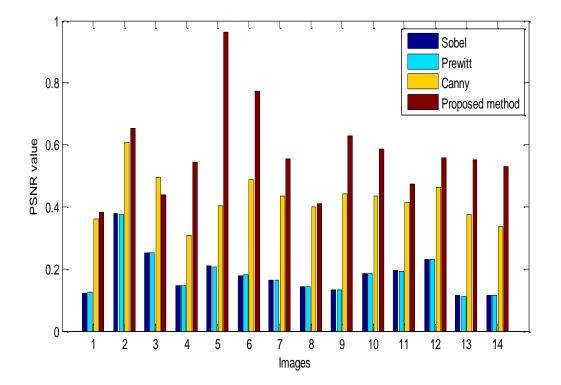


Figure 4.13 Bar chart of PSNR values of results of different edge detection algorithms and proposed method for edge detection.

4.6 Discussion and Conclusion

In this chapter, the proposed algorithm is designed for edge detection in historical images using Cellular Automata. A basic method of image processing called edge detection is used to locate edges or boundaries in a picture. For many applications, such as computer vision, object recognition, and image segmentation, edge detection is crucial. For edge detection, a number of methods have been developed, each with unique advantages and disadvantages. It is observed that the proposed algorithm is suitable for the mural images and has potential to detect edges of multiple objects within image. In order to determine whether the proposed algorithm is correct, a number of tests were run on a variety of images in MATLAB. It is anticipated that compared to earlier algorithms and methodologies, the suggested algorithms provide acceptable results to obtain a greater level of precision for edge detection for images and are more space-efficient. The test images were subjected to statistical analysis, which produced favorable results in all dimensions. In cellular automata, use of simple XOR logic gates makes this method less complex and fast due to parallel processing of computations.

Chapter 5

INPAINTING USING SURF DESCRIPTORS

5.1 Introduction

This chapter addresses problem 3, which is discussed in chapter 1. Art and cultural heritage represent key elements that define human identity as these artifacts represent the most important medium for the transfer of history between generations and civilizations. The value and attractiveness of these artifacts are tightly tied to their physical condition and the availability of their metadata. Unfortunately, a large portion of these assets are in a degraded state or their history is lost. Digital Image inpainting is the art of repairing an image that gets defected while capturing it or during its transmission digitally without user intervention by using intelligent algorithms and techniques [18, 19]. Inpainting is done by estimating the values of missing pixels to recreate the defected region. Image inpainting finds its place in numerous applications of computer vision and image processing. Repairing photographs and restoration of old films to remove scratches and defects is being done since ages. Inpainting or interpolation involves the application of sophisticated algorithms to remove defects and reconstruct the image in a non-detectable manner. The objective of image inpainting is not to recover the original image, but to create some image that has a close resemblance with the original image. Image inpainting can be used in cinema and photography for removing defects like scratches, and dust spots from images (called deterioration) and inpainting is used for distorted images as shown in Figure 5.1. It can also be used for manipulation in images like removing some object from an image or correcting the red-eye effect [135].

PDE based inpainting methods depend highly upon the surrounding information around the target region and are prone to high visual inconsistency [136].

In this chapter, patch-based inpainting approach is adopted for the reconstruction of a defected image. An algorithm is proposed for automatic selection of matching patch for inpainting based on Speeded up robust features (SURF) of the image. This method overcomes the dependence on connected or adjacent pixel information to interpolate missing image portions as is done in exemplar-based methods. Defected image undergoes pre-processing to identify actual region for completion and its local salient features are determined using SURF algorithm [137-139].

Some applications of Image inpainting are as following:

- Image inpainting finds its place in numerous applications of computer vision and image processing.
- Repairing photographs and restoration of old films to remove scratches and defects is being done since ages.
- Used in cinema and photography for removing defects like scratches, and dust spots from images, correcting the red-eye effect.
- Manipulation in images like removing some object from an image to create special effects.
- Cover up the seams in image quilting.

5.2 Related Work

Texture synthesis, i.e. producing new instances of texture from a smaller sample is capable of inpainting images that contain several texture areas. It fills larger regions more accurately. Image quilting [43, 140] is one of the first patch-based texture synthesis algorithms developed by Efros and Freeman. The usual approach to exemplar-based inpainting is to progressively fill in blocks on the boundary of the inpainting region using matching blocks in the known region of the same image [16, 57, 61]. A combined approach [140] known as image completion or image reconstruction uses features from both the techniques to inpaint real images.

Several feature detectors have been proposed in past. Harris [13] proposed a feature descriptor by making use of corner and edge information but this method was easily affected by scale and illumination conditions. Gao Jing et al. [141] proposed an improved version of Harris corner detector to overcome its problems.

Lowe and David [142] proposed a method called Scale-invariant feature transform (SIFT) which uses a Gaussian filter for detecting local feature points. The complexity of SIFT algorithm is too high and requires a lot of time which makes it difficult to be used in real-time applications. The formation of an Eigenvector is highly dependent on the accuracy of the direction of primary extraction, which can also lead to the inaccurate matching of features. Herbert Bay et al. [137] proposed a novel scale-invariant and rotation-invariant detector and descriptor named SURF (Speeded-Up Robust Features). Matching algorithms based on image features are widely used because they have low computational complexity and high robustness.



Figure 5.1 Example of damaged images need inpainting

5.3 Background

5.3.1 Patch-based Image Inpainting

A texture is defined as some visual pattern on an infinite 2-D plane which at some scale, has a stationary distribution [143]. Texture synthesis based inpainting algorithms sample the texture from the region outside the region to be inpainted. It has been demonstrated for textures, repeating two-dimensional patterns with some randomness. Texture synthesis, i.e. producing new instances of texture from a smaller sample, is capable of inpainting images that contain several texture areas. Image inpainting algorithms based on Structural Synthesis try to recreate the structures like lines and object contours. These are generally used when the region to be inpainted is small. They focus on linear structures, which can be thought of as one-dimensional patterns such as lines and object contours.

Patch-based image inpainting fills larger regions more accurately. The resulting larger grid structure is easily noticeable even if the samples are tiled seamlessly. This distorts the perception of the actual texture. Texture synthesis fails to rectify scratches and lines on images. Patch-based methods give poor results when it fails to find a patch in the surroundings to inpaint the missing region. Template matching involves managing and accessing a huge amount of database of images.

Detecting regular patterns automatically is a very challenging task. Regular patterns can be quite complex and multi-scale, involving intricate details. Detecting such patterns may require advanced algorithms and feature extraction methods capable of capturing both global and local characteristics. In this chapter, our method uses a robust local feature extractor to obtain salient features from the input image called Speeded Up Robust Features. Image features are the information that specifies the structures in an image like points, edges or corners. These features play an important role in performing several computer vision processes on the image. Obtaining these features in an image is the first computational task on the image.

Feature detection involves various methods for finding abstract image information. A local decision is made at every point whether there is a feature of a given type or not. Some of the commonly known edge feature detectors are Sobel, Prewitt, and Canny. Among these canny detects all possible edges in the image. Corner detection is generally used in motion detection, object detection, image mosaicing, and image stitching. Corner detectors are very

redundant and not very robust but still have the ability to identify the same corner in multiple similar images under various transformations like different lighting, translation, and rotation. Harris operator is one of the basic corner detection methods due to its rotation invariance, localization accuracy, robustness to noise, and straightforward mathematical formulation. It remains a valuable tool in various computer vision and image processing applications, including feature matching, object tracking, and image registration. Features from Accelerated Segment Test (FAST) corner detector has high computational efficiency and high-speed performances which makes it suitable for various machine learning and real-time video processing applications.

Information about the region, which is not given by an edge detector or corner detector, is obtained by blob detection methods. Convolution is the most commonly used blob detection method. Some of the primitive uses of blob detection include segmentation, texture analysis and object recognition.

A considerable amount of image processing is required to extract salient features after the feature detection process and is known as a feature vector or feature descriptor.

5.3.2 SURF

Image features are the information that specifies the structures in an image like points, edges or corners. These features play an important role in performing several computer vision processes on the image. Speeded Up Robust Feature is an algorithm used mostly for computer vision applications such as Image registration, camera calibration, object recognition, image retrieval and many more [144]. SURF uses an integer approximation of determinant of Hessian blob detector to detect interest points. Hessian matrix has high performance accuracy. A blob-like structure is detected at locations where the determinant is maximum. A descriptor vector of length 64 is constructed using a histogram of gradient orientations in the local neighborhood around each interest point. In a grayscale image I, for a point $X \leftarrow (x, y)$, the Hessian matrix $H(X, \sigma)$ in X at scale σ is defined in (1).

$$H(X,\sigma) = \begin{pmatrix} L_{xx}(X,\sigma) & L_{xy}(X,\sigma) \\ L_{xy}(X,\sigma) & L_{yy}(X,\sigma) \end{pmatrix}$$
(1)

Where, matrix elements define the convolution of the Gaussian second order derivative with the image I in point x. A local decision is made at every point whether there is a feature of a given type or not.

5.4 Proposed method

Firstly, defected image is pre-processed to identify the region for inpainting called the target patch φ_p and its local salient features are determined using SURF algorithm. Secondly, these feature points are matched to global key points of the remainder image to obtain a patch that has almost similar feature orientations or similar feature vector.

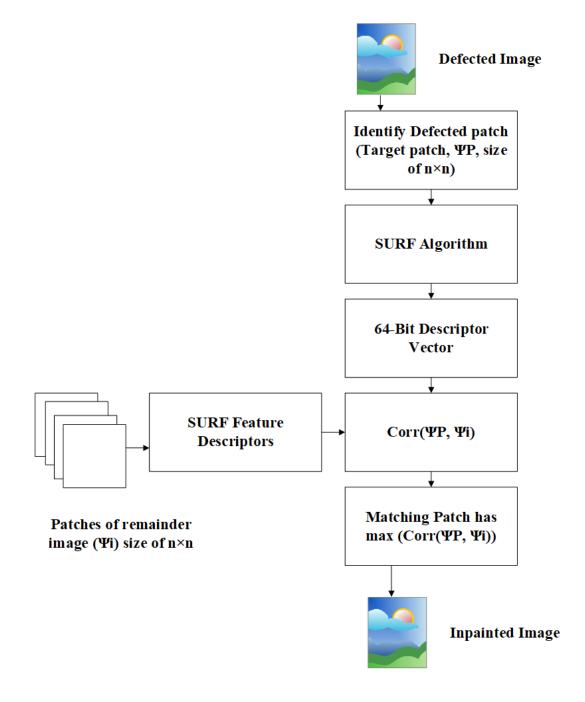


Figure 5.2 Flow diagram of the proposed Algorithm

Feature vector matching is performed based on measuring the correlation between the target patch and other overlapping patches φ_i of the remainder image. Thirdly, the matched patch is mapped over to defected image in a way that looks reasonable to the human eye.

The matching patch is very similar to the target patch and fits well into the surrounding of the defected region. Figure 5.2 represents a flow diagram for the proposed method. The similarity measure of target patch (ψ_p) and matching patch (ψ_i) is given by (2).

$$\varphi_P \sim \varphi_i = max(corr(\varphi_P, \varphi_i)) \tag{2}$$

 $\forall \varphi_i$ patches of $n \times n$ size from the remainder image where the value of *i* depends upon the size of the image and the size of the target patch.

The proposed algorithm for inpainting uses features and key points surrounding the defective region to create the missing image. Defected image comprised of regular texture and some missing region which needs inpainting to rectify and enhance the test image. The proposed method finds the most suitable patch which fits into the missing region. Following are the steps of the proposed algorithm:

5.4.1 Identify the target patch

- a) Locate the missing region and consider a window of size n×n across this region such that it gives sufficiently enough SURF features.
- b) Identify the target patch by locating the defected region for inpainting.
- c) Obtain salient features and descriptors of the target patch using SURF algorithm as shown in Figure 5.4 (a)-(c).
- d) A descriptor vector of length 64 is constructed using a histogram of gradient orientation in the local neighborhood around each keypoint.

5.4.2 Patch matching

- a) Divide the remainder image into several overlapping patches of the same size as that of the target patch and obtain SURF feature descriptor vectors for every patch.
- b) Now, one by one compute the correlation between the feature matrix of target patch and all overlapping patches.

c) A highly correlated patch is found suitable for filling in the missing region of the target patch as illustrated in Figure 5.4 (d) and (e).

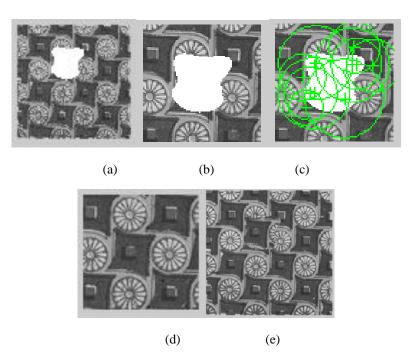
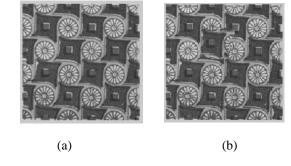
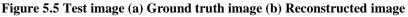


Figure 5.3 Demonstration of algorithm (a) Input image (b) Target patch (c) SURF features of target patch (d) Matching patch (e) Reconstructed image.

5.5 Experimental Results

The proposed method is performed on grayscale images of PSU dataset- Regular Textures databases in an environment of 64-bit (win64) MATLAB version R2015a. All input images are in grayscale. The inpainted image when compared to ground truth distortion-free image as a reference gives structural similarity index (SSIM) approaching to value eqal to one as shown in **Figure 5.5** and Table 5-1. SSIM index is calculated to measure the accuracy and quality of the restored image and its decimal value lies between -1 and 1. The proposed method





reconstructs the image in a way that looks reasonable to the human eye with high accuracy and maximum similarity with ground truth images.

| S.No | Original image | Distorted image | Reconstructed image | Structural Similarity index (SSIM) |
|------|----------------|-----------------|---------------------|---|
| 1 | | | | 0.9145 |
| 2 | | | | 0.9428 |
| 3 | | | | 0.9199 |
| 4 | | | | 0.9357 |
| 5 | | | | 0.9381 |

 Table 5-1
 Measure of Structural Similarity Index of reconstructed test images.

Some Studies on Enhancement of Images of Historical Importance

| 6 | | \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ \$ | 0.8998 |
|----|--|--|--------|
| 7 | | | 0.9483 |
| 8 | | | 0.9457 |
| 9 | | | 0.8790 |
| 10 | | | 0.9420 |

5.6 Discussion

In this chapter, an algorithm is proposed for automatic selection of matching patch for inpainting the missing region by using the SURF features of the image. This method overcomes the dependence on connected or adjacent pixel information to interpolate missing image portions. Matching algorithms based on image features are widely used because they have low computational complexity and high robustness. The SURF method (Speeded Up Robust Features) is a fast and robust algorithm for local, similarity invariant representation and comparison of images. The results shown in Table 1 indicate that the proposed method is efficient enough to interpolate the pixel values in a defected region without depending upon its adjacent pixels for interpolation. The measure of Structural Similarity Index of reconstructed test images has been proved to be nearing to one which implies that the proposed method finds the most suitable patch fitting into the missing region. The proposed method is applied to test images of PSU dataset-Regular Textures database and reconstructs the image in a way that looks reasonable to the human eye with high accuracy and maximum similarity with ground truth images.

5.7 Conclusion

Matching algorithms based on image features are widely used because of their low computational complexity and high robustness. An algorithm is proposed for automatic selection of matching patch for inpainting the missing region by using the SURF features of the image. This method enables the interpolation of missing image portions without relying on connected or adjacent pixel information.

Chapter 6

CONCLUSION AND FUTURE WORK

6.1 Summary of the Work

Image enhancement, edge detection and image inpainting play an essential role in digital image processing as it is required in the field of artificial intelligence, object recognition and pattern recognition. Chapters are based on image enhancement, edge detection and image inpainting proposed and organized in the thesis.

To achieve thesis objectives (refer to chapter 1), we have studied traditional methods of image processing and proposed algorithms for contrast enhancement, edge detection and image inpainting to preserve images of historical importance. We recapitulate the features of this investigation and the results obtained by proposed techniques in the following points: -

Chapter 3 is proposed to improve the contrast of all the pixels within an image so as to minimize the information loss and obtain maximum information from the input image. DWT, SWT, gamma correction and fuzzy systems are the prime components of the chapter. Contrast enhancement through adaptive gamma correction is done not directly upon intensity values but on the approximation coefficient values obtained after 2-D transforms. Two models are proposed in chapter 3, using wavelet transform properties. Model 1 uses the properties of adaptive gamma correction. In contrast, Model 2 is based on a fuzzy system where the fuzzy rule-based systems in concealed with the proposed algorithms for the contrast enhancement of the image and two algorithms are proposed in model 2. To evaluate the performance of the proposed models, PSNR, MSE, entropy, mean and SSIM tests are applied and the results of the proposed algorithms are compared to the existing algorithms clearly indicate that the proposed methods' results contain maximum structural details.

Model 1 is based on DWT and adaptive gamma correction and adaptive gamma correction prevents the resultant image to get washed out in high-intensity regions. Since every image's coefficient values are different, an adaptive gamma correction method is devised to bound the gamma-corrected coefficient values within a range so that inverse transforms result in the efficient reconstruction of an enhanced image.

Model 2 improves the contrast of the overall image in such a way that under-exposed areas are enhanced with different values of gamma and over-exposed areas in the image are enhanced with some different gamma values using fuzzy systems. This method is proposed to minimize the information loss and obtain maximum input image information. In the proposed algorithms, the selection of gamma correction is done adaptively depending upon a fuzzy inference system.

Histogram spread is used to compare contrast enhancement results with other state-of-the art methods and it indicates that the proposed methods produced more promising results. Further, two algorithms are proposed, Algorithm-I is based on the RGB color space model and Algorithm-II is based on CIELab colour space.

- a) In Algorithm-I, a novel algorithm is proposed based on the fusion of contrast corrected images to prevent the situation in which gamma corrected image appears to be patchy due to abrupt change in gamma value for adjacent patches.
- b) Further in algorithm II, the CIE L*a*b color model is used along with the fuzzy system and it overcomes this problem of patchy image and results in a more smooth and clear output image. Algorithm-II are used on several historical images to enhance the contrast in images.

Edge detection, which determines the boundaries of foreground and background objects in an image, is an essential pre-processing step in image processing, computer vision, and machine learning applications. In chapter 4, the concept of finite state machine is explored and cellular automata is deployed to achieve parallel processing for edge detection. Transition rules are applied to simultaneously update the values of each cell represented by four most significant bits. The proposed algorithm in chapter 4 is verified by computing results of Mendeley Dataset images. Existing edge detection methods are complex to implement and fail to produce satisfactory results in case of noisy images. The results obtained by proposed methods are compared with results of existing edge detection techniques by evaluating MSE

and PSNR values which indicates promising performance of the proposed algorithm. Evaluation of test images show that proposed method exhibits better performance even for noisy and cluttered images.

Chapter 5 is proposed for image inpainting in regular texture images using the concept of SURF. A masked image highlighting the degraded or missing regions is generated automatically by performing simple pre-processing operations. Target region, i.e. the missing region which needs inpainting undergoes the speeded-up robust features (SURF) extraction process to describe the features present in the neighborhood of the missing area. The matching is done by evaluating the correlation between the two patches. The size of the target patch and the patch used for inpainting varies depending on the size of distorted region. Patch-based methods give poor results when it fails to find a patch in the surrounding to image the inpainting region. The proposed algorithm is applied to test images of PSU dataset-Regular Textures database and reconstructs the image in a way that looks reasonable to human eye with high accuracy and maximum similarity with ground truth images. Measure of Structural Similarity Index of reconstructed test images has been proved to be nearing to one. The results indicate that the proposed method is efficient enough to interpolate the pixel values in a defected region without depending upon its adjacent pixels for interpolation.

6.2 Future Work

- 1. Creating a database for Historical images which covers all types of mural images captured in different lighting conditions.
- 2. Frequency transforms and nature-inspired algorithms can be applied to get better results with the proposed algorithms.
- 3. The thesis work can be carried upon real-time applications, where we can utilize algorithms to generate better results with hardware simulation.
- 4. Cellular automata can be explored more and other existing automata rules can be applied in the area of image processing.
- 5. In patch-based inpainting, the patches can be discovered automatically by using machine learning algorithms.

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