Digital Restoration of Damaged Mural Images

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CHAPTER 1

INTRODUCTION

1.1 Introduction

As the time passes, the paintings or murals that are made up of materials, can suffer damage. To protect them for a long period of time, they are coated with a varnish layer to protect them. The atmospheric conditions, temperature variations, humidity and sunlight can affect the varnish layer of painting or murals. After a long period of time, the painting color is degrades and seems to be brown or black filter or amber because the transparency of varnish layer becomes clouded and discolored. Few old paintings or murals suffer from breaks in the substrate material, the paint, or the varnish layer. These patterns can be caused by drying, aging and mechanical factors and known cracks or craquelure. Due to Age cracks the supporting canvas or wood-panel of the painting can suffer from non-uniform contraction that can stresses the layers of the painting or murals. Due to the consequent shrinkage of the paint and evaporation of volatile paint components, Drying cracks are made up. Vibrations and impacts on painting can cause painting deformation, hence mechanical cracks result in painting or murals.

The overall visual appearance of old paintings or murals can degrade by the phenomenon of Varnish oxidation. The degradation such as Smoke and Dirt deteriorate the situation even more. These above degradation results as the color faint and the mural appears black. It happens mostly in Church, where candle smoke degrades painting colors. Due to this degradation, the artistic value of a painting also degrades. To remove this oxidation layer, there are many conservation experts; they performed this removing process of oxidation very well. But this process is time-consuming as well as not reliable. This cleaning process became quite difficult due to different prevailing environmental conditions and the chemical properties of different types of varnishes to select the appropriate cleaning process quite. A trial and error approach is implemented on the murals to cleaning the oxidation. In this process, the chemical cleaning substances are applied in small regions of the painting. Then after the most one will be subsequently utilized to clean the whole painting.

These cracks on murals deteriorate the perceived image quality. On digitized murals, we can use digital image processing techniques to detect and eliminate the cracks.

Digital image processing is widely used in all scientific fields to analyze, preserve and restore artwork. In present scenario, Art work restoration is a very demanding field which requires highly considerable expertise. As the passage of years, a number of defects appear in murals like the development of cracks, scratches, discoloration of the varnish layer, accumulation of dust, dirt, smoke on the surface of the painting, loss of paint, etc. Hence, the restoration process of such old degraded murals include stabilization, surface cleaning, the removal of discolored varnish, the repair of tears and punctures, filling areas of paint loss, and expert retouching. Chemical cleaning of old murals is analogous of Digital processing on the old murals. Therefore digital image processing techniques can help art conservators and restorators for cleaning of murals.

In Digital image processing techniques one can restore color and estimate the original appearance of a painting, without using of extensive chemical cleaning treatment of its surface.

1.2 Motivation

In the process of Wall painting restoration on can restore old and damaged wall painting which have cracks, fold marks ,dark or white spots etc. up to their original or a near-original condition.

The motive of restoration of murals is to conserve our esteemed symbol of culture and history. For the ethical values of our future generation, there is a need to preserve murals so that future generations could see them and learn from our culture. The wall paintings help a human to express his culture from the earliest beginning to present day. The deterioration or destruction of these wall paintings may cause a great loss to our cultural heritage. During volcanic eruption their painted coat gets collapsed with each other or in earthquakes, a large number of murals get destroyed. [1].

Wall paintings may suffer destruction due to some other unfavorable weather conditions. In dry environment, due to natural drying such as loss of water, cracks and non-uniform contraction come in existence. These unwanted cracks in wall paintings results in poor quality of perceived image. Some other deterioration like smoke and dust degrade the appearance of murals. This degradation results on painting such a manner that colors of paintings may get faint or seems to be black or brown [2]. As every color has faded to some extents so the color fading is common problem in the old wall painting [3]. So there is a need to restore the faded color of painting. It is necessary to improve or enhance the color of image, to enhance the overall quality of the image. One can use different types of color encoding techniques to enhance the color of wall painting and remove the local deformities in the wall paintings. There is another serious problem with murals that pixels may lost their color and turned to white values. Some other problems which degrade the quality of the wall painting are folding lines, scratches. So it is necessary to recover paintings which are affected by such problems. Restoration is a process of recover the linearly degraded image. Some oil paintings can lose some points on the image to white spots that are very important to be recovered to maintain good overall appearance of the image. To conserve and restore murals one may need different methods and technology, the specialization focuses on specific procedures used during the conservation and restoration of murals based on multidisciplinary knowledge.

1.3 Background Literature Survey

One most popular tool for image and video synthesis and analysis is Patch-based sampling method. This method include image reconstruction and editing, texture synthesis, image stitching and collages, image and video completion, summarization and retargeting, new view synthesis, morphing, noise removal, super-resolution and more. In today’s scenario texture synthesis is an active research topic in computer vision both as a way to verify texture analysis methods, as well as in its own right. Potential applications of a successful texture synthesis algorithm are broad, including occlusion fill-in, lossy image and video compression, foreground removal, etc.

In psychology, statistics and computer vision, texture analysis and synthesis has had a long and great history. In 1950 Gibson pointed out the importance of texture for visual perception [4], but it was great achievement for work of Bela Julesz on texture discrimination [5] that introduced the way for the development of the field. Julesz proposed a technique where two texture images will be perceived by human observers to be the identical if some appropriate statistics of two images matches. This technique proposed that, picking the right set of statistics to match and finding an algorithm that matches them, are two main tasks in statistical texture synthesis.

Formerly Giakoumis et al. do some works on wall painting restoration, which includes the following. He [6] removes the cracks from the Mural image. Top hat transformation was used to detect the local minima for the same purpose. The brush strokes that are misidentified in wall painting image as cracks can remove through the MRBF neural network. In computer system [7] wall paintings were restored from their fragments. Matching algorithms was used for restoration.

A paper “Digital color restoration of old paintings” [2] were presented by Pappas, .M, & Pitas, .I. In this paper techniques for restoration of color of murals were presented. The physical and chemical changes degrade the appearance of murals. Color of murals was fainted through different factors such as aging, dust, smoke and some natural phenomenon such as earthquakes, dry weather and volcanic eruption. A Black or Brown spot results on wall paintings. The colored regions of murals were cleaned up chemically and then patches of digital images are digitized. The purpose of this paper was to do color transformation on entire image with the help of colored sample images. The RGB values can be produced by Image acquisition systems i.e. scanners and camera devices etc. One can use different techniques without chemical clean up treatment to estimate the visual appearance of actual wall painting. To simulate the actual appearance of murals, there are five color restoration methods (Mean sample matching, White point transformation, ICP approximation, linear approximation, and RBF approximation). To recover the actual appearance of murals different types of digital restoration techniques were used as well as small chemical process are used on its surfaces. He gets satisfactory results by performing the same simulation on no. of different murals. The white point transformation and linear approximation generate the best result but small computational requires in all methods.

In 2001, a paper “Digital image processing in painting restoration and archiving” [8] were presented by Nikolaidis, .N & Pitas, .I. Three basic applications of digital image processing were presented in this paper. First was crack restoration. Second was the restoration of color and third was mosaicing of images which are partial. To color restoration of murals linear approximation and the white point transformation methods were used. For effective choice of transformation function linear approximation was used. In white point transformation the object under different lighting conditions look different and the dirty samples was obtained easily. For achieving and classification of paintings a database management system was introduced which was very helpful. This database management system has user friendly GUI which works on user defined SQL queries. One can access the database through SQL queries.

Morphological top- hat transformation was used for crack detection. To eliminate cracks from background the thresholding operation was used. Median filters are used for crack filling. He presented a digital achieving system in this paper.

In 2002, a paper “Contour-shape based reconstruction of fragmented, 1600 B.C. wall paintings” [7] was presented by Papaodysseus .C, Panagopoulos, .T, Exarhos, .M, Triantafillou, .C, Fragoulis, .D, & Doumas, .C. In this paper, author proposed a technology in which the murals turned over in fragments then fragments was photographed. The contours of these fragmented images are obtained by computer. Then proposed techniques and fragmented contours were compared. To achieve the estimation of initial image, the authors introduce an approach which extracts maximum information from the contours of fragmented parts. The impressive murals of the Greek island Thera (Santorini) were painted in the middle of the second millennium B.C. In this paper, a new elevated approach was introduced for the computer-aided reconstruction of the impressive murals. These murals have been excavated in fragments, and as a result, their reconstruction may be extremely attentive and a long process. Therefore, a proper system has been developed based on the defined technique, to facilitate and expedite this method. In this method, every fragment is photographed, its image is send to the computer to obtain its contour, and, then, all of the fragmented contours are compared in a manner proposed herein.

Another paper, “Identification of geometrical shapes in paintings and its application to demonstrate the foundations of geometry in 1650 BC” [9] was introduced in 2005 by Papaodysseus .C, Exarhos .M, Panagopoulos .T, Triantafillou .C, Roussopoulos .G, Pantazi .A & Doumas .C. In this paper, the authors introduce an approach to determine whether a handmade shape fitted into given geometrical prototype. To achieve the above goal, three mathematical criteria are defined; two of them are statistical in nature and another one is based on fuzzy logic. The application of those approches to the important Late Bronze age murals, the inner walls are decorating which are constructed excavated at Akrotiri, Thera, shows the spirals which are portrayed on images of wall paintings correspond to Archimedes spirals with exceptional accuracy. In this paper the technique was proposed together with a set of original criteria to show the specific shape in a painting that has probably been drawn by using geometrical method. In this paper, Pattern recognition methods and related criteria were introduced. This approach only employed on the tharan murals which can be applied to any painted shape. The main objective of this paper was to determine the geometrical shapes or curves, which adjust a given equation in paintings.

Later on, in 2006, Giakoumis .I, Nikolaidis .N & Pitas .I presented a paper “Digital image processing techniques for the detection and removal of cracks in digitized paintings” [10]. In this paper, the authors proposed an integrated strategy for crack detection and filling in digitized paintings. The outputs of the morphological top-hat transform are threshold to detect the cracks. Then, the thin dark brush strokes which have been mystified as cracks are removed using either a semi-automatic procedure based on region growing or a median radial basis function neural network on hue and saturation data. Finally, with the help of order statistics filters or controlled anisotropic diffusion, crack filling is performed. The approach has been shown to perform excellent on digitized paintings suffering from cracks. The approach has been applied for the virtual restoration of images and was found very compelling by restoration experts. However, there are certain future improved aspects of the proposed approach.

Another paper, “Image and pattern analysis of 1650 BC wall paintings and reconstruction” [1] was presented in 2008 by Papaodysseus .C, Exarhos .M, Panagopoulos .M, Rousopoulos, .P, Triantafillou. C, & Panagopoulos .T. To reconstruction of murals, image segmentation and pattern analysis was used in this paper. The color image segmentation method is used in this paper, to decay many problems which provide the good estimation of initial fragments which were depicted.

Pattern matching techniques were used for reconstruction of murals. The murals typically reconstructed from the thousands of fragments which are scattered within excavated sites. Many depictions occur in fragments of murals which manifests non uniform color decay and cracks. Sometimes extraneous material is also added in fragments of murals. The image segmentation technique provides the good approximation of depiction of fragments so it is used. The image segmentation technique defines the color region and region border of depicted fragments.

In 2008, a paper was presented by Pnevmatikakis .E, & Maragos .P i.e. “An inpainting system for automatic image structure-texture restoration with text removal” [11]. The authors suffer with two main problems that are inpainting problems and problem of finding text inside digital images. The main aim of this paper was to finding text inside digital images. There are two main Inpainting technique i.e. structure inpainting and texture inpainting.

Structure inpainting is generally used to define important parts of images like boundaries, edges etc. Texture inpainting is only used to define text data printed on the murals. The morphological algorithm is used to link Structure inpainting and Texture inpainting. In Morphological algorithm, pixel that represents the text characters is captured. Hence inpainting region were known as output. An automatic system is developed for the image restoration and text removal for this purpose. So there is no need of user interface for image restoration and text removal. This system is more advantageous to select the area which is inpainted manually. Previously inpainting systems were not detected the region manually.

Several techniques have been introduced for detection and removal of cracks in digitized paintings, in a paper, "Image processing methods for the restoration of digitized paintings"[12], that was presented in 2008 by Gupta .A, Khandelwal .V & Srivastava .M . Cracks not only degrade the quality of murals but also question its authenticity. A morphological methodology (MAO) is proposed in this paper which is a variant of recently published morphological methods for detection of cracks. After identifying cracks, a modified adaptive median filter (MAMF) is used to fill the cracks. The numbers of neighborhood cracks pixels of the identified crack pixel define the order of the median filter to be applied on identified crack pixel. This approach of identification and elimination of cracks in digitized paintings is shown to be very effective in preserving the edges also.

In 2009, Rousopoulos .P, Arabadjis .D, Panagopoulos .M, Papaodysseus .C, & Papazoglou .E presented a paper "Determination of the method of drawing of prehistoric wall paintings via original methods of pattern recognition and image analysis" [13]. In this paper a method of construction of prehistoric painting was enforced. The approach proposed a method that perform preprocessing of the borders of the figures showing within the mural, determines the patterns repetitions within the border of the represented components, Classification of those repeated patterns into correct geometric prototypes and curve fitting.

In 2011, Naik .P.K., Nitin, N., Janmeja, A., Puri, S., Chawla, K., Bhasin, M., & Jain, K presented a paper "B-MIPT: a case tool for biomedical image processing and their classification using nearest neighbor and genetic algorithm" [14]. Due to inhalation of tobacco smoke, a high rate of expression of Endothelin protein in the placental cell is highly regulated and results to placental abnormalities subjected to birth failure. The algorithm developed using Image Processing; Genetic Algorithms (GA) and Nearest

Neighbor algorithm (NN) automates the study of these Endothelin proteins to assist pathologists and lab technicians in achieving a more efficient and faster diagnosis. The conclusions of the present work shows that the image derived features with GA-NN model appear to be a very fast image identification mechanism providing good results, comparable to some other current work done in the literature. For classification of images into active/passive smokers, we have demonstrated the feasibility of combining GA-NN with image derived features. With the success of NN, there are some critical i.e. expanding the image derived features, use of merely statistical techniques in conjunction with the extracted parameters and an adequate and low-noise training set. Apparently, to predict the more specific image, the more definite a training set can be assembled, and the higher predicting power requires for NN.

A paper "Natural images scale invariance and high-fidelity image restoration" [15] was presented in 2013 by Guo, H., Jiang, F., Liu, S., & Zhao, D. In this paper authors mainly introduces scale invariance at three aspects of essence, representation and application. A mural image always contains the same patterns of different scales and dually the same patterns of same scale exist throughout scales of the image. In proposed image restoration algorithm, GMM based scale invariance model was used. In this algorithm, natural image scale invariance and nonlocal self similarity were utilized concurrently. More precisely, multi-scale similar patterns were searched, adjusted by GMM and then 3-D transformed. Local total variation regularizer and nonlocal adaptive 3-D scale invariant sparse representation regularizer are introduced into the minimization function in regularization based framework. Analytical results show that the introduced algorithm achieves more significant performance than the current state-of-the-art schemes.

Another paper "Improving the running time of the nearest neighbor algorithm" [16] were presented in 2013 by Chompupatipong, N., & Jearanaitanakij, K. In pattern recognition, for classifying objects based on the nearest examples in the feature space, Nearest Neighbor algorithm is a well-known method. However, it has major demerit i.e. the sequential search operation which calculates the distance between the probing object and the entire set of the training instances. In this paper, authors introduce a novel approach to accelerate the searching operation in the NN algorithm. This approach consists of two main steps; creating the reference table and searching the nearest neighbor. One can create reference table of the training instances, once in the initial phase and referred periodically by the searching step. This reference table can rapidly reduce the searching time of the NN algorithm on any feature space. The analytical results on five real-world datasets from the UCI repository show a remarkable improvement on the searching time while the accuracy is still preserved.

In 2013, Karianakis, N., & Maragos, P. delivered a paper "An integrated system for digital restoration of prehistoric Theran wall paintings" [17]. To restore missing parts of various sizes and shapes that appear in Theran wall paintings, they implement an integrated system. In this, the seamless image stitching algorithm was used to stitch the missing area and for area extraction and repair, total variation inpainting was used. For elimination of minor defects on the retrieved parts, they used non-local inpainting mechanism. The graph cuts were used for missing area with complicated borders. Initially, a mathematical morphology algorithm was used to incorporate edge information for detecting missing areas.

After studying the various methods of murals restoration, there are many problems in the existing methods. Making fragments of murals is quite a long, time consuming and difficult task. Morphological algorithm detects only the cracks and missing area in the murals. To overcome these drawbacks a new algorithm that is NN algorithm is used that can serve both the tasks of detecting and removing the cracks. So the quality of the wall painting images can be improved.

1.4 Thesis Organization

Following this introduction the remaining part of the thesis is organized as under; Chapter 2 provides the concepts of Mural Images. The chapter 3 describes the techniques or methods of Digital Image Processing applied over Mural Images. Chapter 4 describes the use of coherent texture synthesis applied for the restoration of damaged mural images. Chapter 6 provides the simulation results of coherent texture synthesis applied over damaged mural images. The chapter 7 concludes the work undertaken in thesis and points to possible direction for future works.

CHAPTER 2

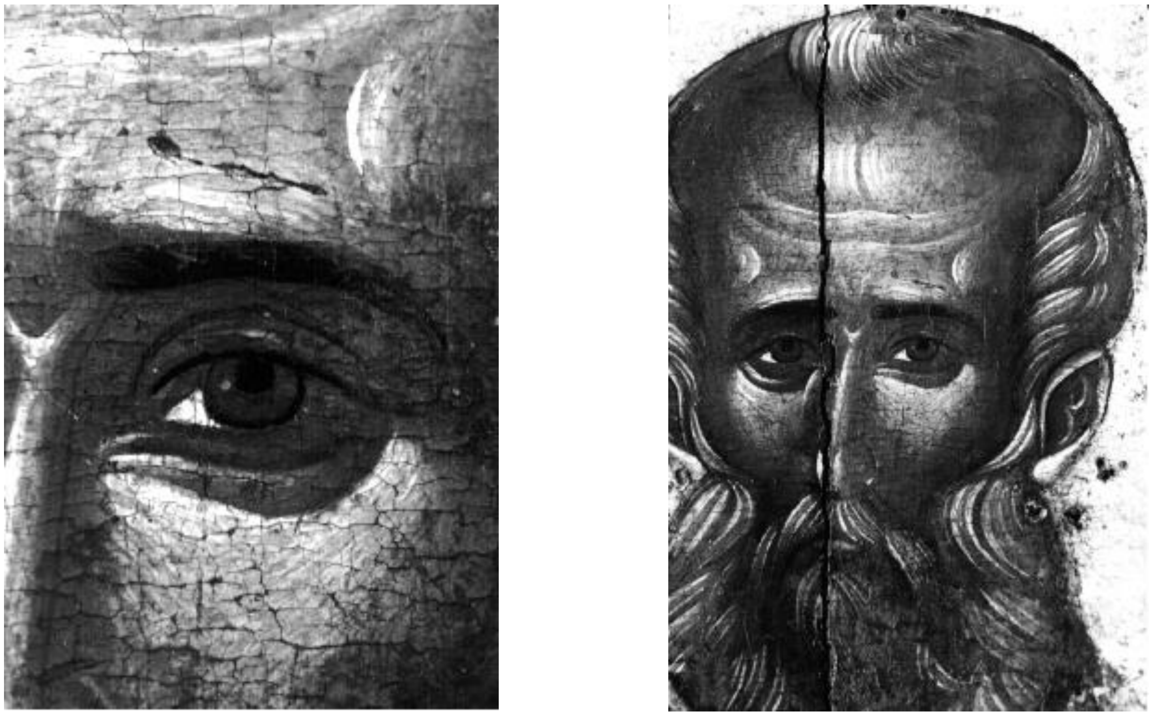
MURAL IMAGES

A piece of artwork painted or applied directly on a wall, ceiling or any other large permanent surface is known as murals. A mural has a particular distinguished characteristic that the architectural elements of the given space are harmoniously incorporated into the picture. These paintings bring ancient art into the public sphere; in this manner they are worthless. Presently these are being degraded rapidly and so it becomes a necessity to preserve what we have right now and also to restore it digitally so that we may have an idea of possible original appearance.

Figure 2.1: Ancient Mural Paintings.

2.1 Defects in Mural Paintings

Many old murals, suffer from breaks in the substrate, the paint, or the varnish. These breaks are usually known as cracks or craquelure and can be caused by different factors i.e. aging, drying, and mechanical factors. A non-uniform contraction in the canvas or wood-panel support of the painting, which stresses the layers of the painting, occurs due to aging effect. Due to evaporation of volatile paint components and the consequent shrinkage of the paint, drying cracks occurs. Mechanical cracks result from painting deformations due to external causes, e.g. impacts and vibrations.



(a) **(b)**

Figure 2.2: (a) & (b) Original Mural painting.

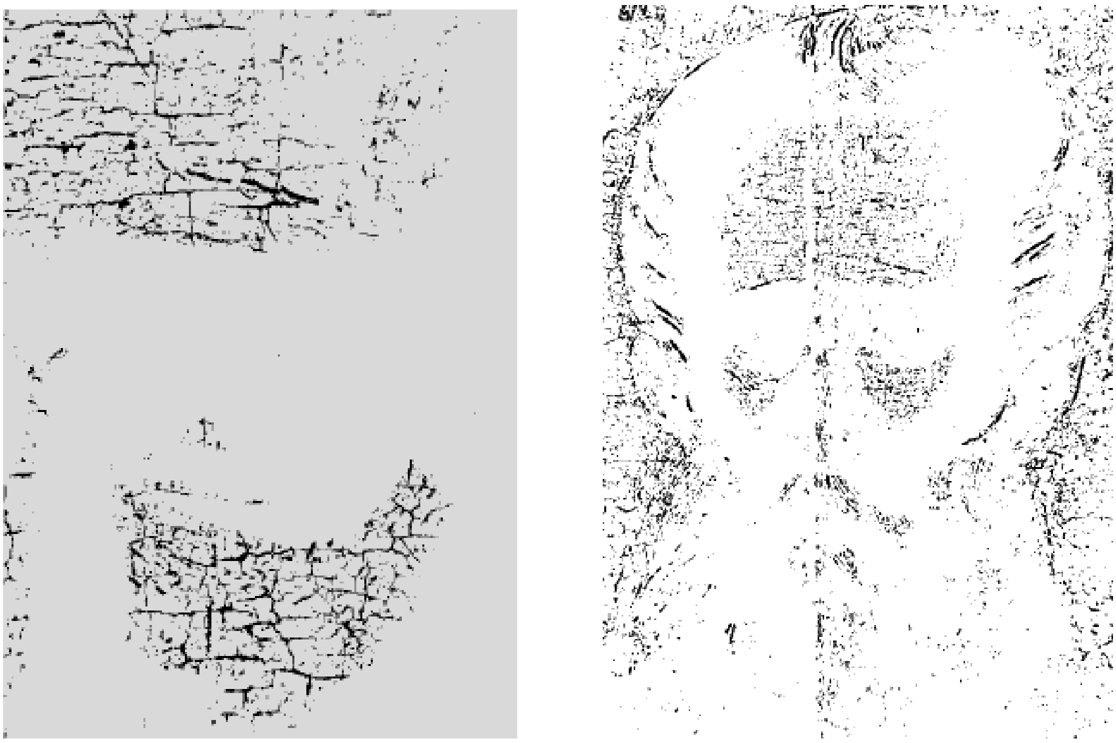
2.2 Crack Detection

The appearance of cracks on murals degrades the perceived image quality. However, Digital image processing techniques can used to identify and eliminate the cracks on digitized paintings. Such as art historians, museum curators and the general public can get clues from ”virtual” restoration that how the painting would look like in its initial state, i.e., without the cracks. And also, for the actual restoration of murals, it can be used as a non-destructive tool. A capable system of tracking and interpolating cracks is presented in [18]. In this paper, the user should manually select a point on each crack to be restored. Other approach for detection of cracks using multi-oriented Gabor filters is presented in [19]. Crack identification and removal are certainly bears certain similarities with methods proposed for the identification and removal of scratches and other artifacts from motion picture films [20], [21], [22]. The above methods rely on information obtained over several adjacent frames for both artifact detection and filling and thus are not directly applicable in the case of painting cracks. Some other research works that are closely relevant to crack removal include image inpainting which deals with the reconstruction of missing or damaged image areas by filling-in information from the neighboring areas, and disocclusion, i.e., recovery of image contents that are hidden behind other contents within an image. Here we assume that the regions where information has to be filled-in are known. Different methods for interpolating information in structured [23], [24], [25], [26], [27] and textured image areas [28] have been developed. The old ones are usually based on partial differential equations (PDE) and on the calculus of variations whereas presently rely on texture synthesis principles. An approach that decomposes the image to textured and structured areas and uses appropriate interpolation techniques depending on the area where the missing information lies has also been proposed [29]. The results obtained by these approaches are excellent. In this paper, authors introduce a technique for the restoration of cracks on digitized paintings, which adapts and integrates a number of image processing and analysis tools. This approach is an extension of the crack removal framework presented in [32]. The approach consists of the following stages:

a) Crack detection.
b) Separation of the thin dark brush strokes, which have been misidentified as cracks.
c) Crack filling (interpolation).

For optimal results, a certain degree of user interaction, most notably in the crack detection stage, is required.

The large variations observed in the typology of cracks would lead any fully automatic algorithm to failure, hence user interaction is unavoidable. All processing steps can be simulated in real time and thus the user can instantly observe the effect of parameter tuning on the image under study and select in an intuitive way the values that achieve the optimal visual result. We can say that only subjective optimality criterion can be used in this case since no ground truth data are available. The opinion of restoration experts that inspected the virtually restored images was very positive.



(a) (b)

Figure 2.3: (a) & (b) Threshold output of the top hat transform

2.3 Analysis of Varnish Layer

The varnish layer is used to protect the painting from abrasion and pollution in the atmosphere. Varnish is transparent in nature but when it applied to the painting, it brings out the colors to the brilliance, but with the passage of time, due to oxidation and deposition of dirt and smoke, the varnish layer becomes opaque, and thus results in a picture being viewed as if through an amber or even brown or black filter.

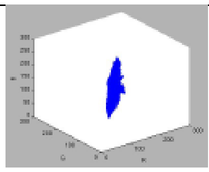
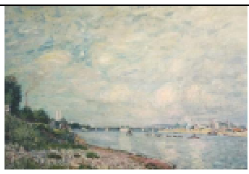
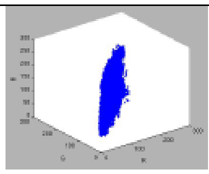
In Figure 2.4, it is shown that, overlapping area has dull and amber look as compared to other region of the painting. When we analyze a number of paintings, it has been observed that due to the dirty varnish layer, the standard deviation and entropy of the image decreases.

A comparative result of standard deviation and entropy of a number of chemically cleaned and old paintings are shown in Table 2.1. The point cluster of old and chemically cleaned paintings in RGB color space is represented in table. The mean color (R, G, B) changes due to the effect of oxidized varnish layer and subsequently results in shifting the origin of the point cluster of the paintings. It is also observed that due to decrement in the standard deviation, the point cluster volume of the old painting also decreased.

Figure 2.4: Effect of dirty varnish layer

Due to decreased point cluster volume, only few colors are available to represent the image results an amber coloration and hiding the vibrant colors beneath. Due to the low range of gray levels available for the image, poor contrast images have a dull look and we can upgrade their appearance by increasing the range of gray levels with the help of histogram stretching. We observe that to obtain the point cluster of the chemically cleaned painting, transformations such as scaling, translation and rotation must have been applied on the point cluster of murals. The point clusters could be obtained in either RGB or Lab color space. Thus, we utilize this concept of applying the various transformations on the given point cluster of the murals and observe its corresponding effect on the murals. In the next section, we show user intervention in specifying the various parameters for scaling and translation and obtain a satisfactorily clean image based on the visual perception.

Table 2.1: Statistics of a pair of degraded and clean paintings

Image	Point cluster	Red Mean	Red Std. Dev.	Red En-tropy	Green Mean	Green Std. Dev.	Green En-tropy	Blue Mean	Blue Std. Dev.	Blue En-tropy
		184.6	20.8	6.032	182.2	19.5	5.825	144	22.7	5.983
		155.9	54.1	7.386	158.2	54.3	7.287	158.0	66.3	7.278

CHAPTER 3

DIGITAL IMAGE PROCESSING IN MURAL IMAGES

Mural Painting are basically the art made on the wall which is the ancient way to express the trend and to sustain its existence for long, till many centuries. It can be the message which is to be conveyed to the further upcoming generations. During the past centuries, all the messages were kept secured and alive by means of mural painting or text can be emboss on leafs, stone, or walls etc, due to non existence of paper. As time passes away those mural paintings became the cultural heritage for that particular society, the images its color quality, clarity also hampered, may also affected by earthquake, storms, weather change and therefore maintaining those heritage became the prime task of the scientists. The study and interpretation of those mural paintings is based on the ability of those scientists to see and understand, as clearly as possible, image details which are affected or hidden through years of weathering or damage by man.

3.1 Digital Image Processing

Digital Image processing is the best possible approach to analyze the obscured region or the hidden facts in the murals and that too without altering the originality of those murals. Digital Image Processing is used to improve the visual appearance of images to the viewer and to prepare images for identification of their remaining features, extending sometimes human vision beyond its natural limitations. Due to advanced accessibility to image processing technology over recent years means that more extensive, powerful and flexible computer applications for detailed image analysis and enhancement are now available to a greater number of scientific disciplines and to users of those are not highly skilled professional in computer-specific, educational background.

Digital image acquisition can be done directly, using a digital camera, or indirectly, using an ordinary camera and scanning the developed film or the printed image or directly transferred to the computer. Although digital cameras are still expensive, their use is preferable because indirect image acquisition can lead to lose the resolution or data integrity. Images are basically a visible spectrum or to specific areas can be analyzed, if some specific filters are used. High quality camera lenses are required to take pictures in the ultraviolet area of the electromagnetic energy spectrum. Broad-band digital cameras or infra-red films are used for images in the near infra-red region or infra-red area of the spectrum. If complete coverage from the ultraviolet to the infra-red area is required, at least two camera bodies, two lenses, four filters and approximately ten differently taken pictures of the same object is required to get the absolute necessity to analyze the murals. The whole procedure is not very convenient. Skill, knowledge and experience are required to make the best use of the photographic equipment and record as much information as possible. The proper uses of computer applications to make the information available in these images are more comprehensive and therefore more valuable.

The level of information present in a digital image depends heavily upon its resolution. The smallest square-shaped unit of the digital image, called a pixel, has to correspond to the smallest drawn detail in the real image, or, even better, to be half its size. Lower resolution leads to loss of information, whereas higher resolution increases computational requirements.

3.2 Image Color Recognition

Pseudo color is a basic approach of monochromatic image transformation to highlight specific details in the image. In this pseudo color code method, each class of pixel values in an image is coded to some color based on a so-called color “Look Up Table". This is a simple method which is widely used in medical and environmental applications. Since the human eyes are much more sensitive to change in color than to change in brightness, the distinctness in features and the number of perceivable details also increases.

For many years the technique of water-spraying mural paintings, to make colors more vivid and highlight different features, has been widely used. The same and even better results are obtained by using computer based histogram transformations of the relevant digital images. A histogram denotes the frequencies of each of the pixel values of an image and is highly useful as an analysis tool. The distribution of various frequencies gives an indication of the possibility of image enhancement. A histogram transformation modifies actual pixel values in the image to output pixel values, according to the particular method, having as a result a rather sophisticated contrast enhancement. An even distribution of the obtained frequencies of pixel values increases the entropy of the image, highlighting details not easily perceivable by the human eye and improving the pictorial information for human interpretation.

3.3 Image Filtering

Filtering of digital images is used to reduce, remove, or amplify specific components of the image. A filter is a technique used to produce an enhanced image, in which each pixel value is calculated as some operation of the corresponding pixel value and its surrounding pixels in the original image. Smoothing filters can suppress unwanted effects; sharpening filters and edge or line detection filters are used to increase the visual interpretability of the image. Depending upon the required results, a matrix of coefficients, by which pixel values in an image are multiplied, has first to be specified. The size of the matrix determines the number of surrounding pixels which are taken into consideration, and has direct effect on computational requirements. To satisfy the specific condition, adaptive filtering is frequently applied, before the input value is replaced by the filtered value in the enhanced image. Numerous of general purpose filters are available. Although there modem software exists that supports user-definable filters, the specification of a new filter, for a particular case of interest, requires much knowledge and experience.

These all filtering processes are applicable to every mural painting for virtual restoration. The image of the mural painting can also be improved, by filling the gaps usually present. A new value can be assigned to pixels of undefined value, which correspond to gaps, using a conditional, digital, filling filter. Capillary cracks, common on most mural paintings, can be successfully removed by applying a smoothing effect, but edge and detail preserving, non-blurring filter, which uses the median value of pixels in the neighborhood, rather than the mean one. The result might not be as aesthetically pleasing as a hand drawn addition, but it has the advantage of being a homogeneous and clearly describable intervention.

3.3.1 Image Rectification

The correction in geometric distortions, resulting from the acquisition process, is often necessary, before the study and analysis of images. This procedure is known as image rectification and is based on modeling distortions, by selecting clearly defined points and specifying what the coordinates of these points would be, in an undistorted image. In most of the church we saw a decorative pattern where rectification is important, because it leads to an accurate representation of the decorative scheme. Geometric patterns and decorative features can be easily studied and correctly drawn to scale.

3.4 Image Registration

Image registration is a method which is gives a relationship between the pixel co-ordinates of an image and a co-ordinate system of reference. If this procedure is not possible, an image to image registration could be applied to perform analysis and comparison of images, which is taken from different positions, under different conditions or in different moments. In this case, one image has to be considered as a "master" and all the others must be registered to that. The procedure is based on locating easily definable points on both the master and the "slave" images. A variety of algorithms can be used to perform image to image comparison and auto-locate reference points present on both images e.g. mean normalized similarity or mean normalized correlation method. Image registration is a prime requirement for multi-channel analysis and for autonomous machine comparison of digital images. Multi-channel analysis is the computer application, which provides a means to extract as much information as possible from the available images of mural paintings. Although, the autonomous machine comparison of digital images, acquired in different moments, forms the basis of a decay monitoring system by the following criteria

a) It should be clearly indicated that the areas of the mural painting which have been changed;
b) New cracks and surface peeling must be located automatically; and,
c) Properly identify the spread of humidity or expansion of mould.

It is evident that colors are always a powerful descriptor and simplifies the identification of details of any painting. Color is a property connected with the ability of objects to reflect electromagnetic waves of different wavelengths. Any color image can be described as it consists of three spectral components which are red (at 700 nm), green (at 546.1 nm), and blue (at 435.8 nm). As the color image processing refers to enhancements and transformations in each waveband. Therefore, all the dull colors of any mural painting can be virtually restored to their former condition by histogram transformations, in each of the color image components.

3.5 Image Capture

Instead of using color film, one could use special camera-lens filters, lenses, and films which allow the acquisition of images in different light bandwidths. Such images, digital or digitized, can be combined to produce a color composite image. The combination of these digital images depends on the accuracy of the image registration of each of the components. The combined image acquires more information, than any directly acquired color image, and correspondingly gives a better indication of pixel- vector differences, than any of the component images alone.

3.5.1 Image Capture Band

In addition to this, any components images in the infra-red band can also provides more information on fungi or humidity problems, and show those details which are invisible to the human eye. There are some possibilities of acquiring images in the ultraviolet band, may leads toward quality restoration, which can give information about the original pigments used in mural painting. Most often, in processing a color image presents two main problems. A hardware requirement increases very rapidly, which depends on image resolution and their possibility of correlation between color image components, which reduces the level of available information.

In cases where correlation between the channels of multispectral images shows poor color separation, the method of producing the first three principal components of the image, on which a color composite is based, may be used. This composite is not a true color representation of the original image, but it can be helpful to highlight some details, which are not easily seen otherwise. Principal components transformation is simply a method, which attempts to improve feature separation, by producing transformed channels, which have minimized correlation.

3.6 Image Interpretation

Interpretation of digital image data on computer is referred to as "quantitative analysis", which is because of its ability to identify pixels, based on their numerical properties. Classification is a method, by which labels may be attached to pixels in view of their spectral character. Some specific computer applications are used to recognize spectral similarities among pixels. The separation of classes of features is image segmentation and it is possible, if their spectral properties determine classes sufficiently well. The limited number of pigments, used in mural paintings, makes it possible to use classification methods to identify areas that are originally painted with the same color, even if the reason of decay and faded pigments make this identification very difficult to the human eye. Conservation problems of the mural paintings, such as humidity, accumulated surface salts, and different types of lichens can be identified as they have different spectral properties. A knowledge base can be constructed slowly, and possibilities of seeking features of known spectral properties are also possible.

Some similarities in mural painting fragments can also be a method of restoration, based upon their patch based correlation.

CHAPTER 4

RESTORATION TECHNIQUES FOR MURALS

The process of restoration of missing or damaged region and removing undesired objects in murals is known as image inpainting, and a good approach of restoration murals with the use of digital image processing. Image inpainting has been widely investigated in the applications of digital effect (e.g., object removal), image restoration (e.g., scratch or text removal in photograph), image coding and transmission (e.g., recovery of the missing blocks), etc. The basic idea is to fill in the lost or broken parts of an image using the surrounding information in such a way that the final restored result appears to be natural to a unknown observer. The analyst has to identify the missing or damaged areas objectively, since these areas cannot be easily classified. These specified regions are called **target regions** and the undamaged parts, whose information is used to repair the target region, are called **source regions**.

Figure 4.1 shows the deteriorating of mural painting and the common denotation which are being used in the inpainting literature. The missing region which is to be filled is shown by Ω and is called the target region, and its boundary is denoted by $\delta\Omega$. The source region, which is not affected as the time passes is denoted by ϕ, which remains fixed throughout the algorithm, supplies samples to fill in the missing regions.

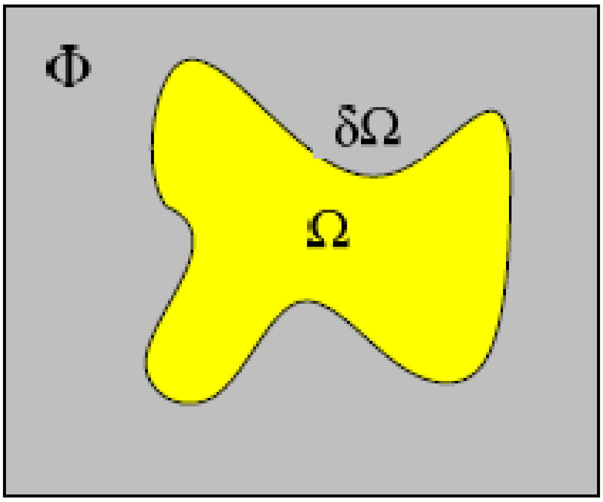


Figure 4.1: Notation diagram: The original image to be filled with target region Ω, its boundary $\delta\Omega$ and the source region ϕ.

4.1 Image Inpainting Technique

Many successful algorithms for image inpainting have been developed in the past decade which can be categorized into the following groups:

a) Diffusion based algorithms.
b) Texture based algorithms.
c) Exemplar and search based algorithms.
d) Sparsity based algorithms.

4.1.1 Diffusion Based Approach

The most fundamental approach of inpainting is the diffusion based approach, in which the missing or damaged region (or **target region**) is recovered by diffusing the image information from the known region (or **source region**) into the missing region at the pixel level. Within the category of PDE (Partial Differential Equation) based methods, there are a several approaches which perform well for piecewise smooth images with sharp edges. These algorithms are well founded on the theory of partial differential equation (PDE) and variational method. Bertalmio *et al.* [29] filled in holes by continuously propagating the isophote (i.e., lines of equal gray values) into the missing region. They are likely to introduce smooth effect in the textured region or larger missing region.

A patch-based diffusion technique based on Beltrami-kernel flow is used in an alternating sequence with a novel patch-based high frequency enhancing method which leads to an edge-sharpening anisotropic diffusion technique which is robust to noise.

4.1.2 Texture Based Approach

The second approach is texture synthesis technique. The basic idea in these methods is to duplicate the information for the source region (**known region**) into the target region (**missing region**) which helps to fill large regions with pure textures and hence, the texture information is preserved.

Texture synthesis based approaches are further classified into two categories:

(1) Pixel Based Sampling.
(2) Patch-Based Sampling.

4.1.2.1 Pixel Based Sampling

In Pixel based sampling method the filling process of target region is performed according to the sample texture size which involves pixel by pixel transformation and consequently the algorithm is designed for reconstruction of mural but this process is very slow.

4.1.2.2 Patch Based Sampling

This algorithm involves block of pixels transformation which enhance the speed of patch-based sampling, but discontinuous flaws between neighboring patches can be seen and therefore it cannot be applied on area with high resolution in murals.

Here are some of the diffusion base techniques which are also analyzed and simulated in this thesis:

(i) Analysis of automatic fast coherent texture synthesis algorithm.

(ii) Using patch-based edge enhancing anisotropic diffusion technique.

(iii) Simulating an interactive mural painting restoration technique based on patch matching.

4.1.2.3 Coherent Texture Synthesis

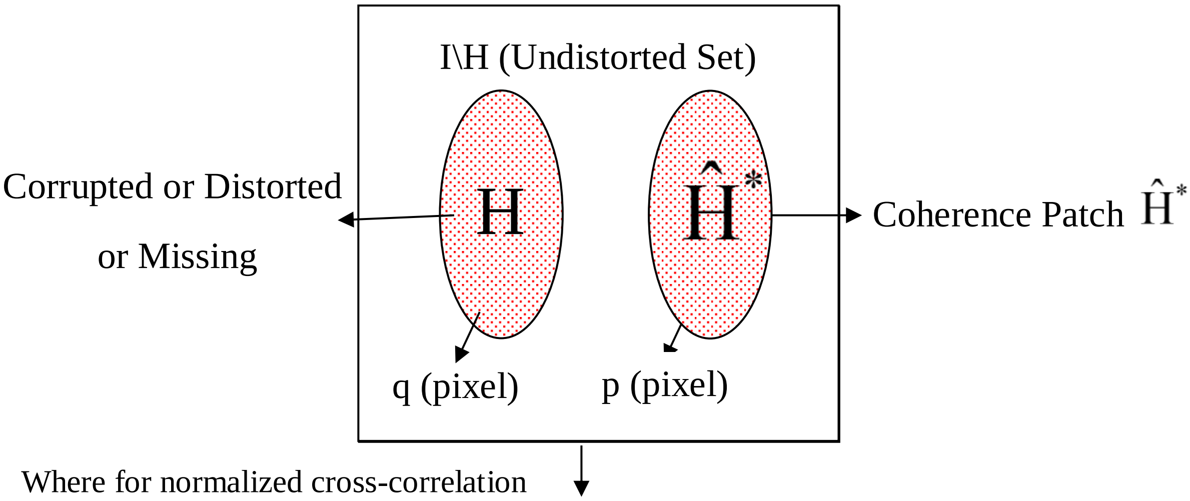
Simakov et al. [30] have suggested a method that the visual data can be summarized using bidirectional similarity which is based on coherence of patches. The global objective function can be used to remove the drawbacks of local inconsistencies by using large patches. In coherent texture synthesis technique the same pattern for synthesizing textures is used by which the missing or distorted part can be redefined or replaced by the coherent part which is the known or undistorted part of the image.

Now, Let us assume an image ***I*** (input image) has some distorted region ***H*** and which is similar to the other part of the image. So, the missing part of the image has coherence with the other part can be replaced by the data $\boldsymbol{H^*}$ which results in the new image $\hat{I}$ which resembles like the original undistorted image region ***I\H***.

So, the above procedure can achieve the maximize function by

$$\left(\hat{I}\middle| I \setminus H\right) = \sum_{P \in H^*} \max_{q \in I \setminus H} s\left(P(p), P(q)\right)$$

Where p and q are pixel set for all distorted and undistorted set simultaneously. ***P*** (***p***) is the patch which denotes the distorted region of the image.



Where for normalized cross-correlation

$$q = q_1, q_2, q_3 \ldots\ldots\ldots q_N$$

$$p = p_1, p_2, p_3 \ldots\ldots\ldots p_M$$

$$p(q) = \frac{q - \bar{q}}{\sqrt{\sum (q - \bar{q})^2}} \text{ and } p(p) = \frac{p - \bar{p}}{\sqrt{\sum (p - \bar{p})^2}}$$

I = Input Image

H = Missing or Distorted region

$\hat{H}^*$ = Coherence Patch Data

I\H = Undistorted Region

Î = New Image

To find the similarity or coherence of the patches the function generated as

Euclidean Distance

$$s\left(P(p), P(q)\right) = \exp\left(\boxed{}\right)$$

It's a correlation function used for the formation of condition of similarity among patches

The objective function is non-linear and therefore the function must be resolved with expectation and minimization technique per iteration. Where for each iteration the coherence of patches results in the similarity of pixel values of '***p***' belongs to $\boldsymbol{H^*}$ and '***q***' belongs to the rest of the image part ***I*\H** will be replaced to maximize the result for the accuracy.

The coherence between patches in ***H*** and rest of the image ***I*\H** according to the equation (1) is maximized if for every pixel value ***p*** belongs to the patch $\boldsymbol{H^*}$ (distorted/damage/missing) patch with all surrounding pixel values $p = p_1, p_2, p_3 \dots\dots\dots p_k$ similar to the pixel color ***q*** with all corresponding location of $q = q_1, q_2, q_3 \dots\dots\dots q_k$ appears in the rest part of the image ***I*\H**.

Therefore, for every iteration, the expectation for getting the maximum similar patch for ***q*** in the unaltered region ***I*\H** for each value of $p \in H^*$.

Let us suppose that $p(q_1), p(q_2), p(q_3) \dots\dots\dots p(q_k)$ denotes the patches in I/H having similarity to the $p(p_1), p(p_2), p(p_3) \dots\dots\dots p(p_k)$ in the H patch. The probability of getting most similar patch will be more while satisfying the condition

$$s_i = s\left(P(p_i), P(q_i)\right) \approx 1$$

Therefore for each iteration and for every point $p \in H^*$ and for all the surrounding patch $\boldsymbol{P(p_i)}$, we need to find out the best possible patch $\boldsymbol{P(q_i)}$ in ***I*\H**. The weights are simply taken as the similarity measure $\boldsymbol{s_i}$ between the corresponding patches $\boldsymbol{p_i}$ and $\boldsymbol{q_i}$.. By using this method the required huge computation of finding the similar nearest neighbor is reduced by compensating it to the approximate nearest neighborhood.

(a)

Figure 4.2: Sample masked Images for Digital mural restoration for applying texture synthesis on the marked region.

4.1.3 Exemplar Based Approach

The exemplar based approach is another inpainting algorithm where the propagation of image information from the known region into the missing region is done at the patch level. This idea is evolved from the texture synthesis approach. Although, the natural images are composed of textures and structures, in which the textures are image regions with homogenous patterns or feature statistics (including the flat patterns) whereas structures constitute the primal sketches of an image (e.g., the edges, corners, etc.) Criminisi *et al.* [31] designed an exemplar-based inpainting algorithm by transforming the known patches into the missing patches gradually. To restore the missing portion in mural with composite textures and structures method, the patch priority is explained to invoke the filling-in of patches on the structure. A cross-isophotes exemplar-based inpainting algorithm was proposed by Wu [32], according to which a cross-isophotes patch priority term was described based on the anisotropic diffusion analysis. A non-local means for the exemplar-based inpainting algorithm proposed by Wong [33]. According to this algorithm, image patch is inferred by the non-local means of a set of candidate patches in the source region instead of a single best match patch. In comparison with diffusion-based inpainting algorithm, the exemplar-based inpainting algorithm performed well for inpainting the large missing region.

4.1.3.1 Algorithm for Exemplar based method

Step 1: For each point ***P*** on the boundary **δΩ**, construct a patch Ψ_p, with ***P*** in the center of the patch.

Step 2: Compute the patch priority ***P***(***p***) : ***P***(***p***) is defined as the product of two terms: a confidence term ***C***(***p***), and a data term ***D***(***p***). Figure 4.1 shows the entire region marked with the notations.

$$P(p) = C(p) * D(p),$$

$$C(p) = \frac{\sum_{q \in \psi p \cap \bar{\Omega}} C(q)}{|\Psi_p|},$$

$$D(p) = \frac{\left|\nabla I \frac{1}{p} . n_p\right|}{\alpha},$$

Where, $|\Psi_p|$ is the area of Ψ_p, α is a normalization factor (e.g., α = 255 typically for a gray level images), n_p is a unit vector orthogonal to the boundary at the point ***p***, and $\nabla \frac{1}{p}$ is an isophote vector. ***D***(***p***) is the linear structure which is to be synthesized first, ans thus transfer securely to the target region, ***C***(***p***) illustrates the amount of the reliable information surrounding to the pixel ***p*** and is initialized to be

$$C(p) = 0, \ \forall p \in \Omega, \quad \text{and}$$
$$C(p) = 1, \ \forall p \notin \Omega.$$

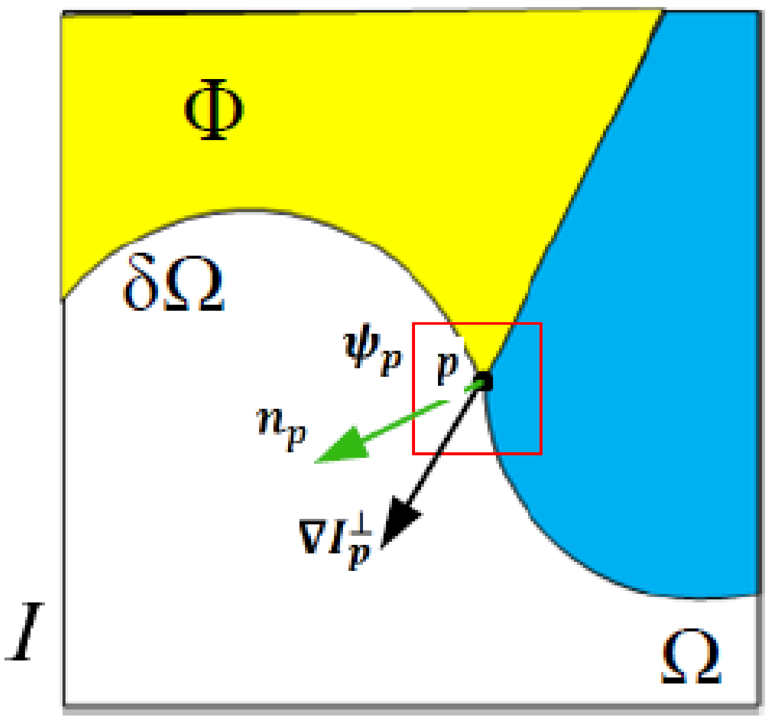


Figure 4.3: Given the patch $\Psi_{\hat{p}}$ for image *I*, n_p is the normal to the boundary at *p*, and $\nabla \frac{1}{p}$ is the isophote vector.

Step 3: Find the patch $\Psi_{\hat{p}}$, with the highest priority being filled in with the information extracted from the source region ϕ (Fig. 3 (a)).

Step 4: Make a global search on the whole image to find a patch Ψ_q having the most similarity with $\Psi_{\hat{p}}$. Formally,

$$\Psi_{\hat{q}} = \arg\min_{\psi_q \in \phi} d(\Psi_{\hat{p}}, \Psi_q),$$

Where the distance ***d*** between two generic patches is simply defined as the sum of squared differences (SSDs) of the already known pixels in the two patches (Fig. 3 (b)).

Step 5: Copy the value of each pixel to be filled in,

$$p' \big| \, p' \in \psi_{\hat{p} \cap \Omega},$$

Using its corresponding position inside $\psi_{\hat{q}}$, (Fig. 3 (c)).

Step 6: Update the confidence term ***C***(***p***) in the area encircled by $\Psi_{\hat{p}}$ as follows:

$$C(q) = C(\hat{p}), \;\; \forall q \in \Psi_{\hat{p}} \cap \Omega.$$

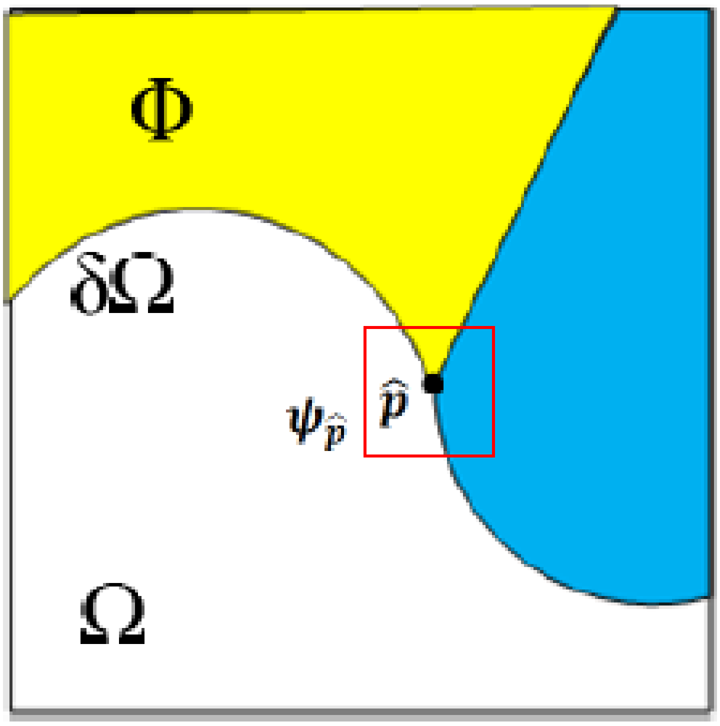


Figure 4.4 (a) Algorithm 1: (a) The patch $\psi_{\hat{p}}$, with the highest priority is found to be filled in,

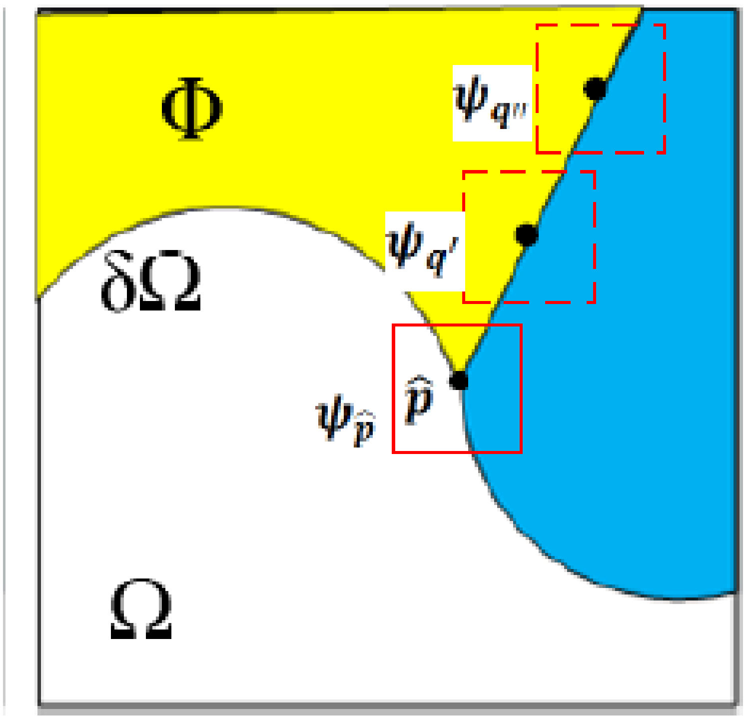


Figure 4.4 (b) Algorithm 1: (b) The most similarity candidate patches with $\psi_{\hat{p}}$, are determined, e.g.

$\psi_{q'}$ and $\psi_{q''}$,

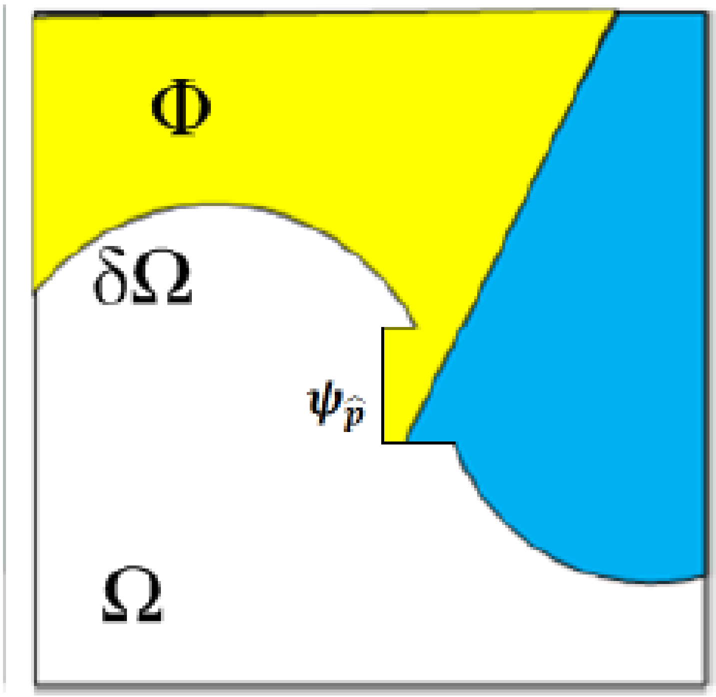
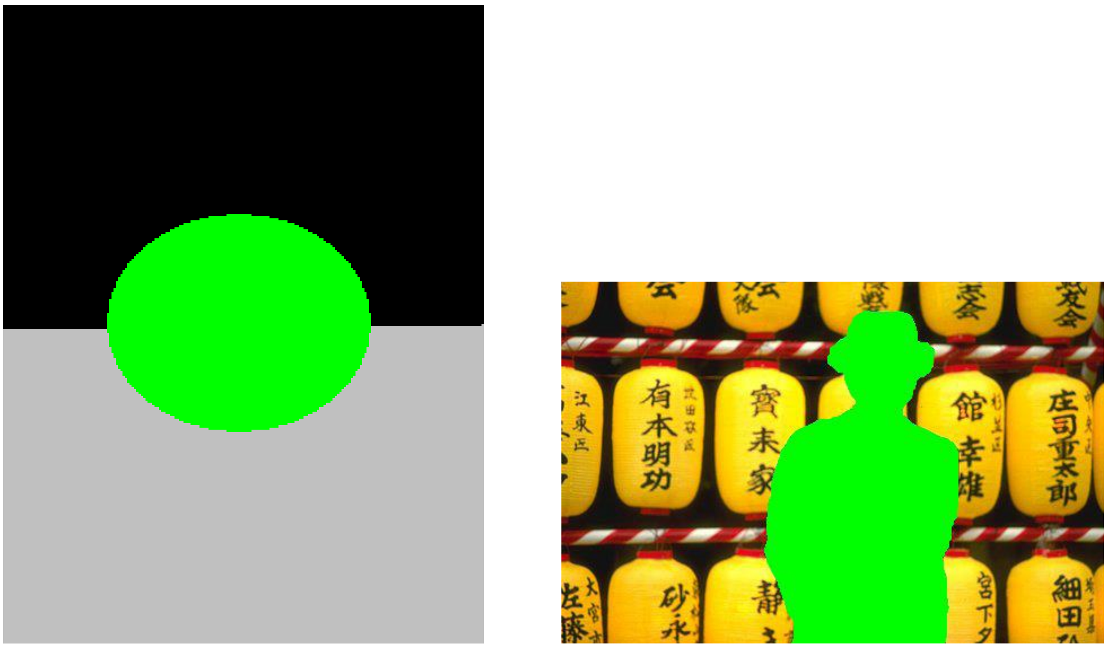


Figure 4.4 (c) Algorithm 1: (c) The best matching patch in the candidate set copied into the position occupied by $\psi_{\hat{p}}$, and thus partial filling of Ω is achieved.



(a) **(b)**

(b)

(d)

Figure 4.5: Sample masked Images for Digital mural restoration for applying Exemplar approach on the marked region.

4.1.4 Sparsity Based Approach

Recent research is based on image sparse representation which has also been introduced for the inpainting problem. In this particular methods, an image is taken by a sparse combination of complete set of transformations (e.g., DCT, wavelet, contour etc.), and then the missing pixels are reproduced by adaptively updating the sparse representation. An approach were proposed by Elad et al [34], where the image was separated into cartoon (structures and texture components), and then represented a sparse combination of the two obtained components by two incoherent components over the complete transformations. This approach can fill the missing regions effectively with structure and texture; it may fail to repair the structure or might produce smoothing. An iterative algorithm based on sparse representation for an image inpainting was proposed by Fadili et al [35]. According to this algorithm the missing samples can be recovered by Expectation Maximization (EM) framework representations. Another exemplar-based inpainting method using a patch sparsity representation was suggested by Xu and Sun [36]. Here they introduced the idea of sparse representation under the assumption that the missing patch could be represented by sparse linear combinations of candidate patches. Then, a constrained optimization model was proposed for the patch inpainting.

According to sparsity approach the patch priority is replaced by structure sparsity, which is basically a collection of neighboring patches with the highest similarities and are distributed in the same structure or texture. Therefore the structures for patches are measured by the sparseness of non-zero similarities to the neighboring patches. The specific patch with non-zero similarity and more sparsely distributed patterns are laid on fill-front due to high sparseness of structures. For the ψ_p patch which is located on the boundary or fill front $\boldsymbol{\delta\Omega}$ with a neighboring patch ψ_{pj} which is defined in the source region, and a neighboring window $\boldsymbol{N(p)}$, with $\boldsymbol{p_j}$ on its center with $\boldsymbol{p}$, being the neighborhood is set. i.e $\boldsymbol{p_j}$ belongs to the set

$$N_s(p) = \left\{ p_j : p_j \in N(p) \text{ and } \Psi_{pj} \subset \bar{\Omega} \right\}$$

Here $\boldsymbol{N(p)}$ should be chosen larger in size as compared to ψ_p.

Now let us suppose $\boldsymbol{P}$ is the matrix to extract the missing pixel value from ψ_p and $\bar{P}$ extracts the already known pixel value from ψ_p than the relation between ψ_p and ψ_{pj} is given as

$$W_{p,pj} = \frac{1}{z(p)} \exp\left(-\frac{\left(d\psi_p, \psi_j\right)}{\sigma^2} \right)$$

where d denotes the mean squared distance of the already known pixels in the two patches, Z(p) is the normalization constant so that

$$\sum_{pj \in Ns(p)} W_{p,pj} = 1,$$

and σ is set to 5

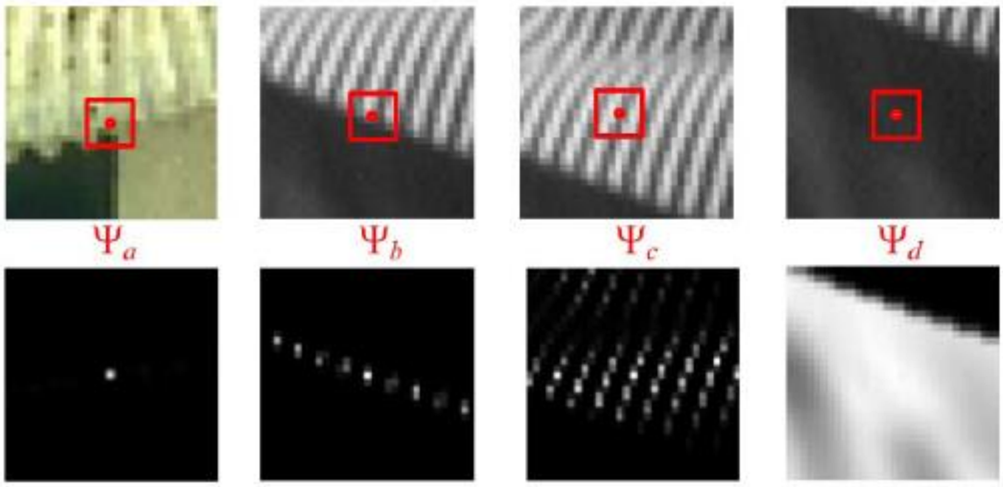
For the patch ψ_p ,the sparseness of most similar patches in the neighboring region $\boldsymbol{N_s(p)}$ is measured by the following equation:

$$P(p)=\left\|\vec{w}_p\right\|_{L_2}\sqrt{\frac{|Ns(p)|}{|N(p)|}}$$

$$P(p)=\sqrt{\left[\sum_{pj\in Ns(p)}\left[w^2_{p,p_j}\right]-4ac\right]\frac{|Ns(p)|}{|N(p)|}}$$

Where $\vec{\Psi}_p$ denotes the vector of elements

$$w_{p,p_j}\left(p_j\in N_s(p)\right), \quad \text{and } |\,.\,|$$



(a) **(b)** **(c)** **(d)**

Figure 4.6: Structure sparsity values of patches on corner, edge and textures. The first row shows the patches in rectangle and their surrounding regions. The similarities of patches ψ_a,ψ_b,ψ_c and ψ_d with their neighboring patches are computed and shown in the second row. The patches ψ_a and ψ_b on corner and edge have the larger structure sparsity values compared with the patches ψ_c and ψ_d in texture regions. (a) Patch on corner. (b) Patch on edge. (c) Patch in texture. (d) Patch in flat region.

means the number of elements and $|\mathrm{N}_p|$ is used to restrict ***P*(*p*)** on the boundary limit in the interval [0,1], although its value is same for different patches. This definition declares the fact that the larger sum of squared similarities in the larger region means larger sparseness. In the following paragraph, the sparseness of patch similarities is called as the ***structure sparsity***.

For defining structure sparsity the following conclusion have been drawn.

Statement 1: The structure sparsity $\boldsymbol{\rho}(\boldsymbol{p})$ for the patch Ψ_p achieves the maximal value $\sqrt{|Ns(p)|/|N(p)|}$ if a single non-zero similarity exists, and it achieves the minimal value $\sqrt{1/|N(p)}$ if all similarities are same and equal $\sqrt{1/N_s(p)|}$.

We observe that $\boldsymbol{\rho}(\boldsymbol{p})$ consistently increases with respect to $W = \sum_{pj \in Ns(p)} w_{p,pj}^2$.

To find the maximum and minimum values of $\boldsymbol{\rho}(\boldsymbol{p})$, we only need to compute the maximum and minimum values of ***W***. Firstly, to find the minimum value of ***W***, we minimize under the normalization constraint $\sum_{pj \in Ns(p)} W_{p,pj} = 1.$. This can be achieved by Lagrangian multiplier method, i.e., maximizing:

$$E(p) = -W + \lambda \left| \left(\sum_{pj \in Ns(p)} w_{p,pj}^2 - 1 \right) \right|$$

It is easy to prove that ***W*** achieves minimal value when $w_{p,pj} = 1/|N_s(p)$ for each $p_j \in N_s(p)$.

Then we maximize ***W***. Due to the fact that $0 \le w_{p,p_j} \le 1$, so $W \le 1$. The equality holds when only a single $w_{p,pj}$ equals to 1, and all the other similarities equal to 0. So ***W*** achieves its maximal value 1 when only a single similarity is nonzero and equals to 1.

Finally, it is easy to derive the maximal and minimal values of $\boldsymbol{\rho}(\boldsymbol{p})$ by inserting the maximum and minimum values of ***W*** into (3).

This above explanation tells that while using structure sparsity algorithm we achieves its maximum and minimum values when the patch similarities are distributed in the sparsest and smoothest fashion respectively, and in the neighboring patches the structure sparsity increases in compare to the sparseness of patch's nonzero similarities.

It is now investigated that how the structure sparsity measures the structure confidence for different types of patches in the natural images. For the patch on the 0-D corners (see Figure 4.6 (a)), it is an important distribution within the local region; therefore, it has the highest structure sparsity. Due to the sparsity of image edges, the patch on 1-D edge (see Figure 4.6 (b)) has similar patches which are sparsely distributed along the same edge; therefore, they have higher structure sparsity. However, for the texture patches shown in Figure 4.6 (c) and (d), have similar patches in the 2-D local regions; and therefore, they have structure sparsity of smaller values. As per the pathway of structure sparsity, the patches located at structures (mostly corners and edges) have higher priority for patch inpainting as compared to the patches in texture regions.

CHAPTER 5

SIMULATION RESULTS & DISCUSSION

We have implemented our algorithm using MATLAB 7.6 on a Microsoft Windows 7 Operating System with 4GB of RAM and a 2.6-GHz core i3 Intel processor. Mex codes for exemplar approach have also been used to speed up the process. In most of the simulation we have seen that even with reasonably large images our system responses in almost real time. Only for high frequency diffusion process it takes few seconds to generate the output.

While using our sample Figure 5.1 (a) to (g), we have shown the result of coherent texture synthesis approach which have been proposed by Simakov et al. [30] for the problem of image inpainting/completion. The results are appreciable and it is clear from the images that by using this algorithm, the coherent information from the whole unaffected portions of the images are retrievable The structures are preserved in the coarser scale and the coherence information is embedded during the refinement into fine structure at the larger scale. After selecting a source region we search for similar patches and the synthesized texture would have coherence with the source region only. With this little user intervention, the performance of texture synthesis improves significantly and user can get more control over the synthesizing process. While looking over the results, the process is repeated again by selecting more refined source region until the synthesized texture is not satisfactorily obtained. In the consecutive figures 5.1, the results are appreciable and coherent texture synthesis performs well for repeated iterations and refinement. In the Figure 5.1 (a), the top row contains original image and figure 5.1 (b) shows the masked region (in green) where texture to be generated. At each step the masked portion of the target window is filled by the texture that is coherent to the texture in the source window. In figure 5.1 (c), we see the step-wise texture pattern to fill the marked region, where the steps are defined by the portion of marked region inside the target window. Figure 5.1 (d), (e), & (f) shows the images after replacing the synthesized texture on the damaged region, i.e., after image completion after applying the coherent texture synthesis technique. In figure 5.1 (g), (h) we display the original and the restored images.

Fig. 5.1 (a): Original Mural Painting

Fig. 5.1 (b): After masking the damage region

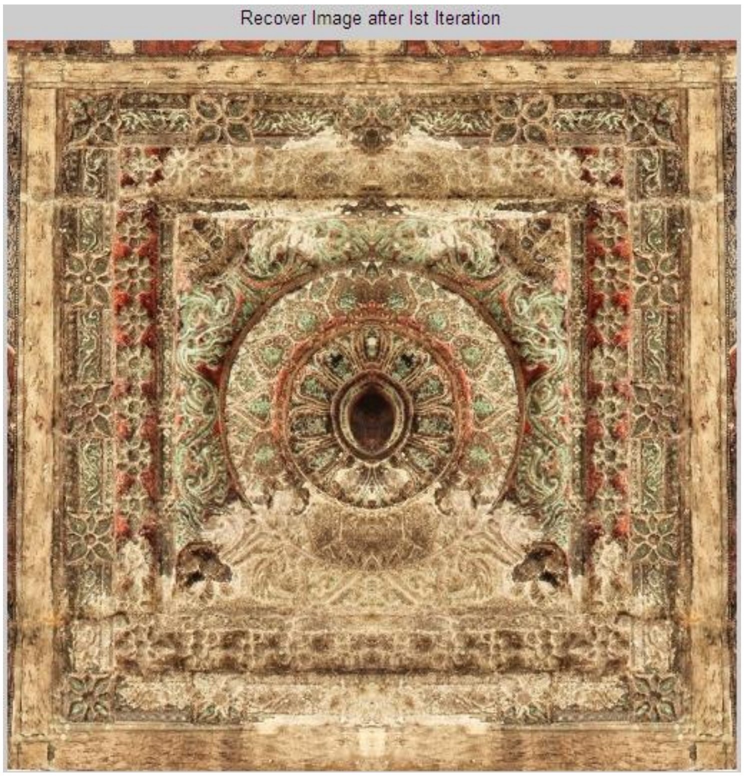


Fig. 5.1 (c): Result after Ist iteration

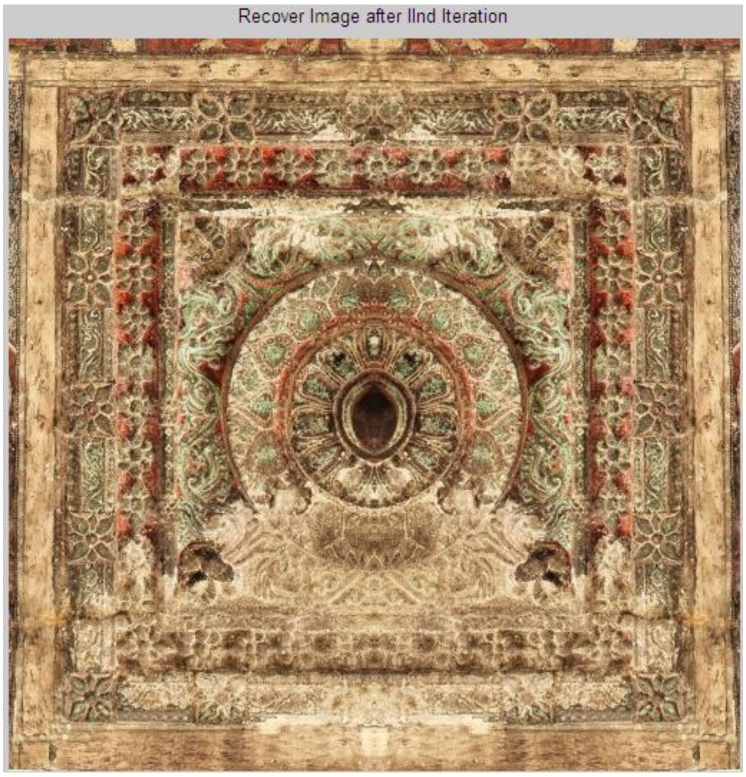


Fig. 5.1(d): Result after IInd iteration

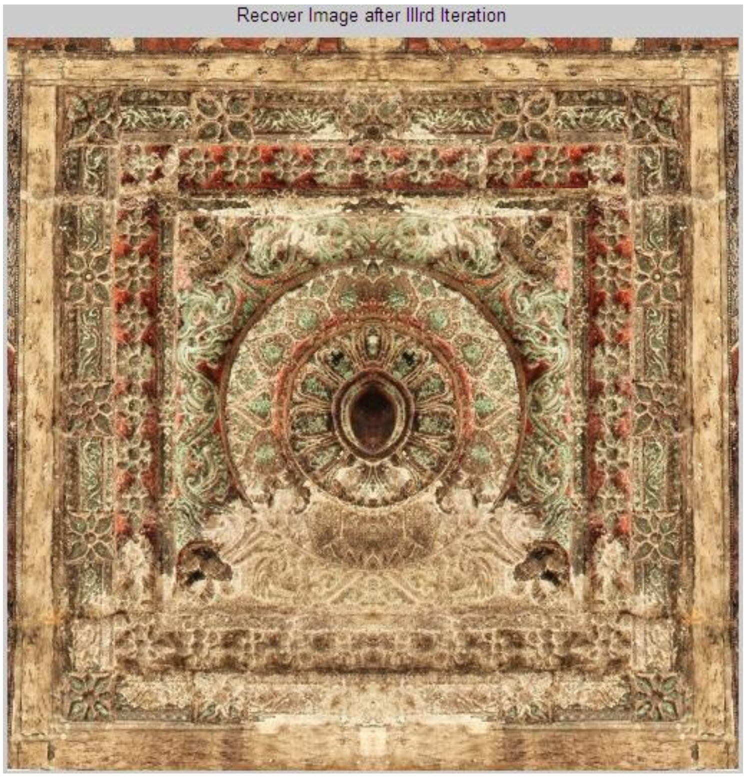


Fig. 5.1 (e): Results after IIIrd iteration

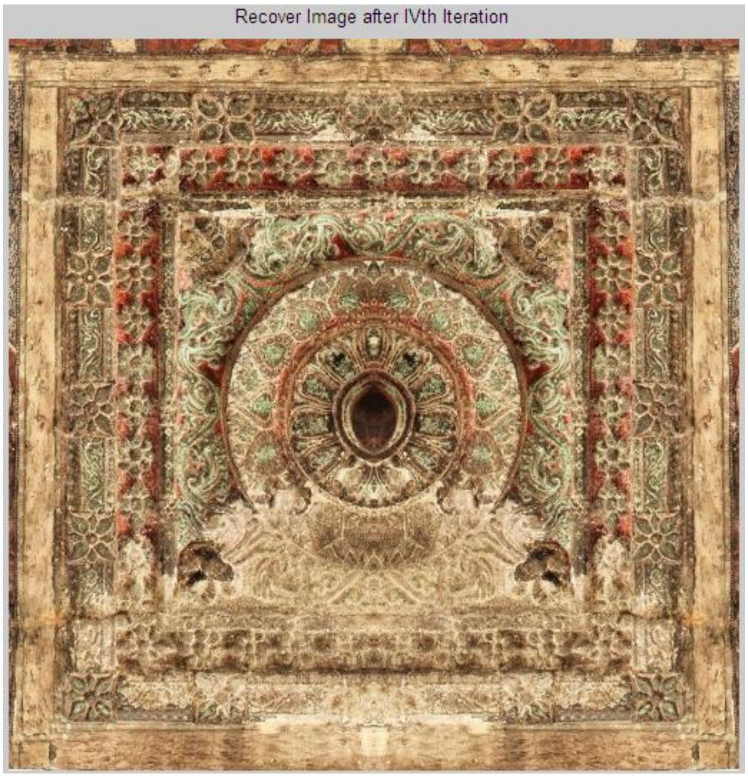


Fig. 5.1 (f): Result after IVth iteration

Fig. 5.1 (g): Result after Vth iteration

Fig. 5.1 (h): Final Restoration of Mural Painting

Figure 5.1: Digital mural restoration: top to bottom are the original image and different steps of proposed texture synthesis on the marked region which leads to the Final output.

We have already seen some results of coherent texture synthesis algorithm. In this section, we present another technique of restoration of mural painting digitally, which we call exemplar algorithm.

Figure 5.2: (a) Image marked with undesired object

Figure 5.2 (b): Image inpainting/completion as an application of Exemplar synthesis: The marked green regions are undesired object which are replaced by exemplar synthesis in the image.

5.1 Effect of Patch Sparsity on Inpainting Performance

In this section, we quantitatively justify the improvement of inpainting performance caused by structure sparsity and patch sparse representation. To this end, we take the traditional Criminisi's examplar-based inpainting algorithm [31] as the baseline, then measure the performance improvement after replacing isophote-based priority [31] by structure sparsity based priority or(and) replacing the texture synthesis based patch inpainting [31] by the sparse representation based patch inpainting.

Figure 5.3: (a) Image marked with undesired object

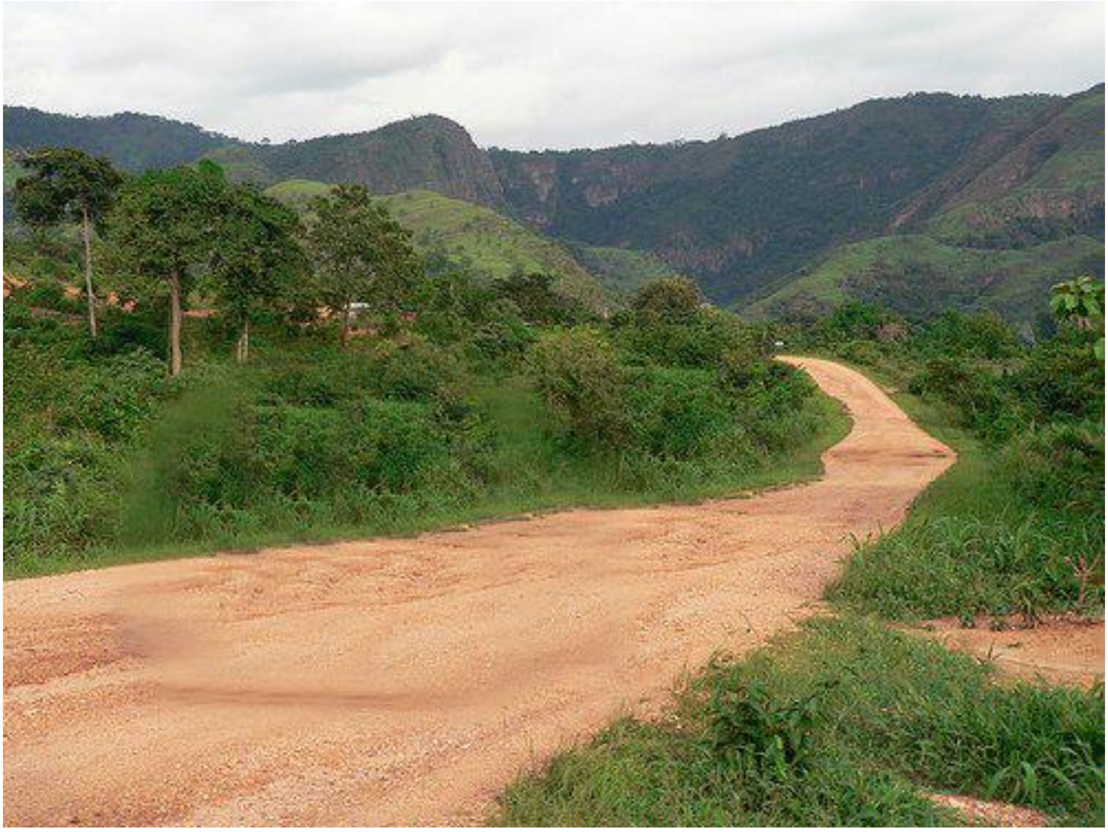


Figure 5.3 (b): Image inpainting/completion as an application of Exemplar synthesis: The marked green regions are undesired object which are replaced by exemplar synthesis in the image.

Figure 5.2 and 5.3 presents more examples for the application of text removal, scratch restoration and object removal.

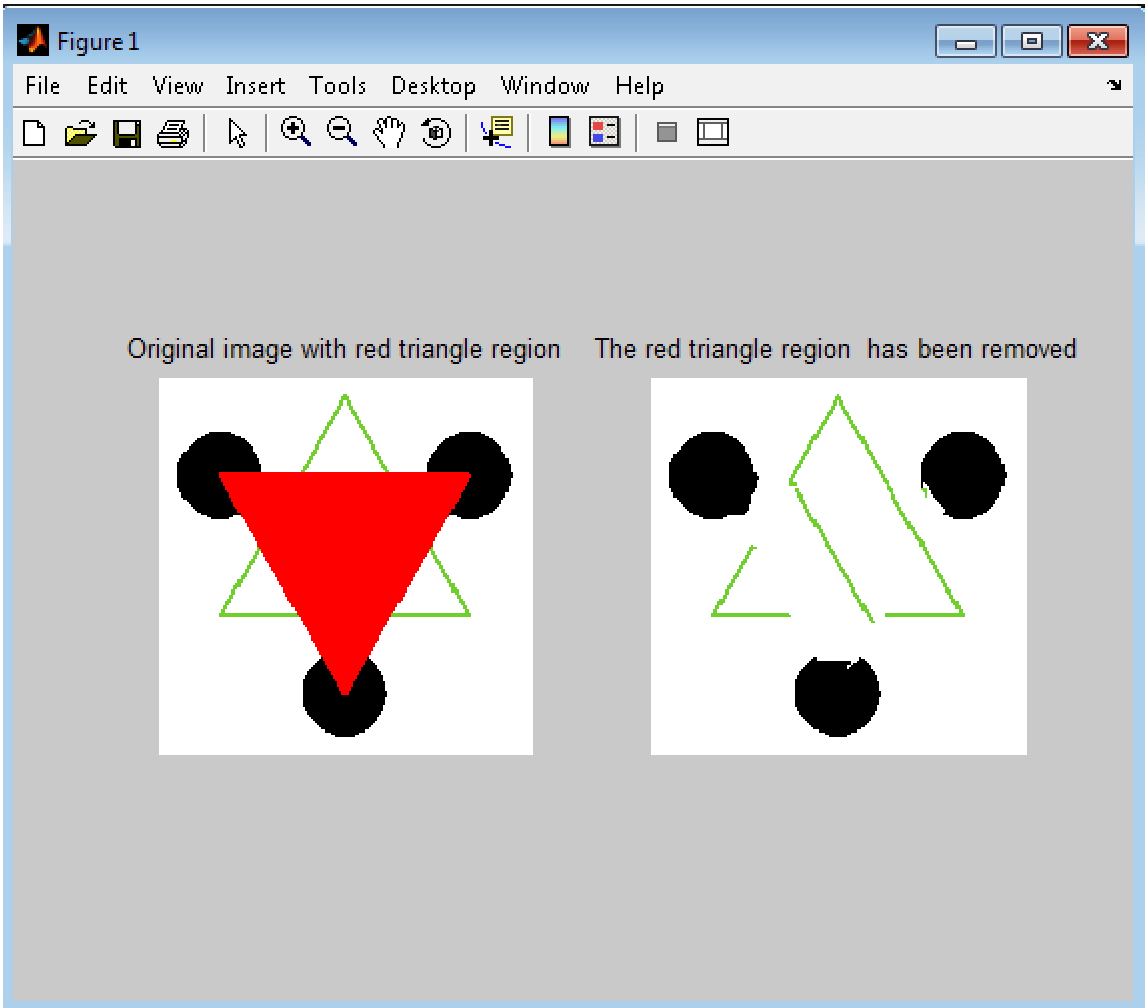


Figure 5.4: Image inpainting/text & object removal as an application of Exemplar synthesis: *Algorithm 1.* Results obtained in original and degraded images, respectively.

The time for processing restoration is

Process Time = 31.0 Seconds

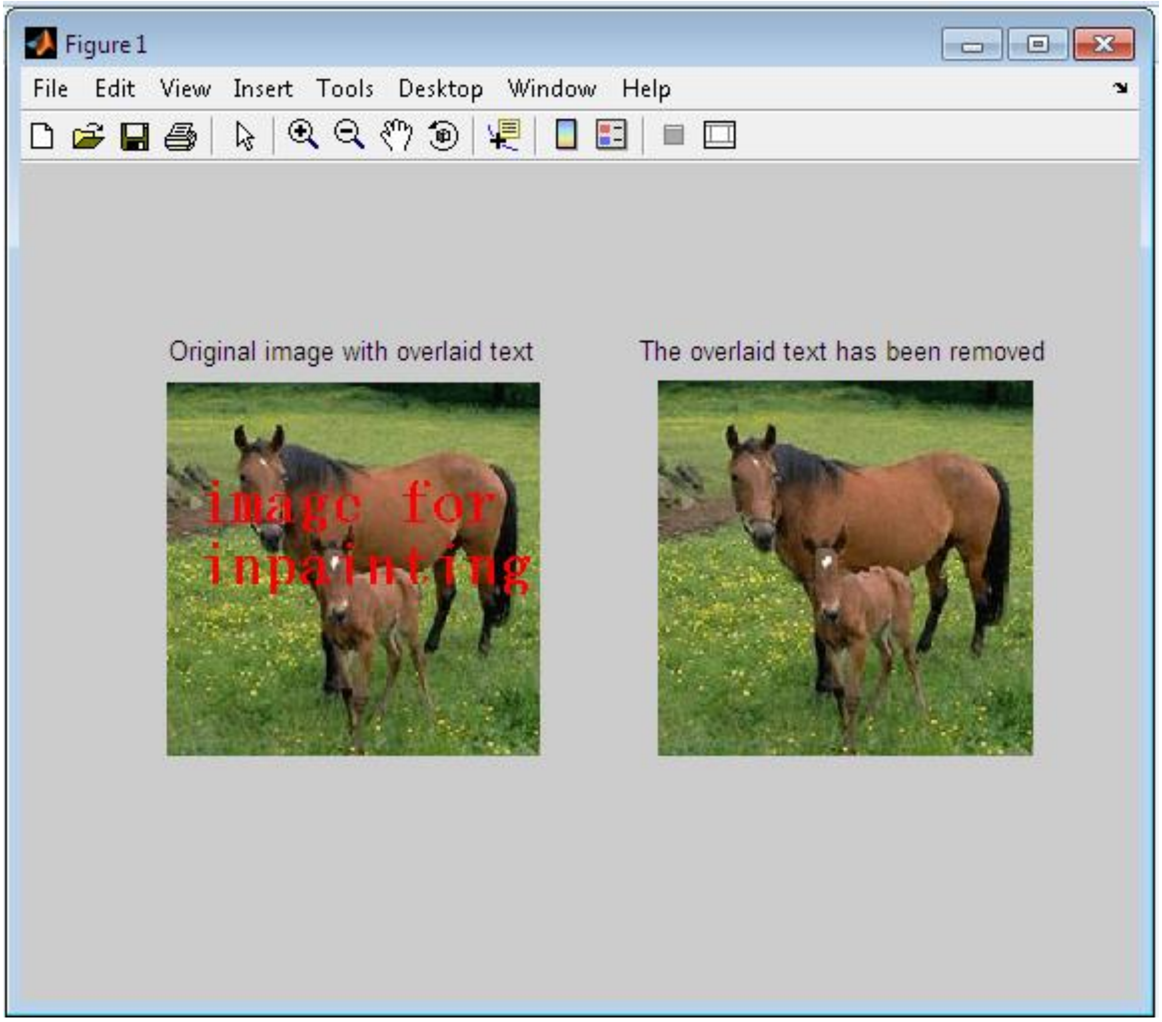


Figure 5.5: Image inpainting/text & object removal as an application of Exemplar synthesis: *Algorithm 1*. Results obtained in original and degraded images, respectively.

The time for processing restoration is

Process Time = 76.4531 Seconds

5.2 Experiments and Comparisons for Object Removal

We now apply the Patch Sparsity and isophote algorithm to inpaint the missing region after object removal. We also compare the proposed algorithm with the related exemplar-based inpainting algorithms. Figure 5.6 shows the simulated results which are appreciable and up to the mark.

The first rows show the original, degraded and restored images, and the second row provides the region of confidence and data term which have been drawn for the corresponding image for object removal respectively show the images obtained by the patch sparsity method [37].

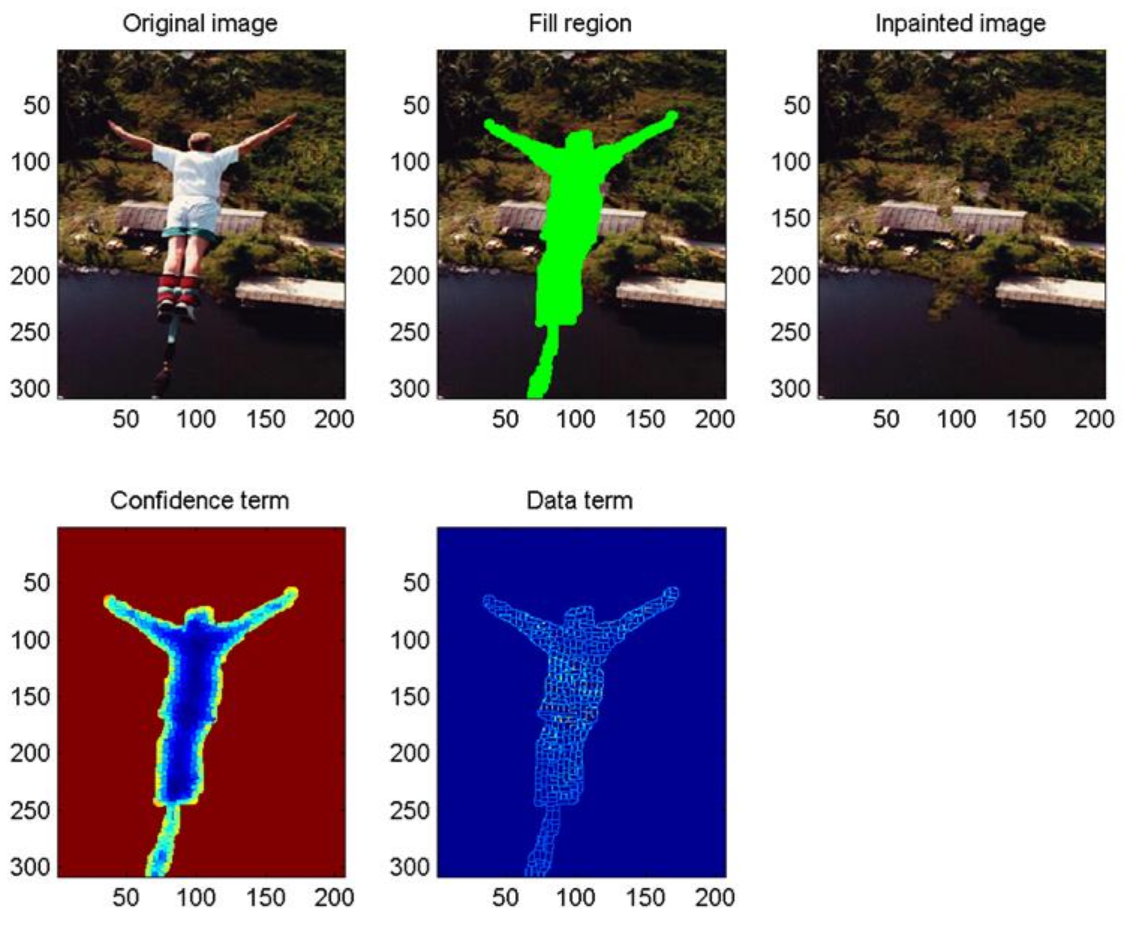


Figure 5.6: Comparison for object removal (a) The original degraded image. (b) The marked image (c) The restored image. (d) The confidence term (e) The data term.

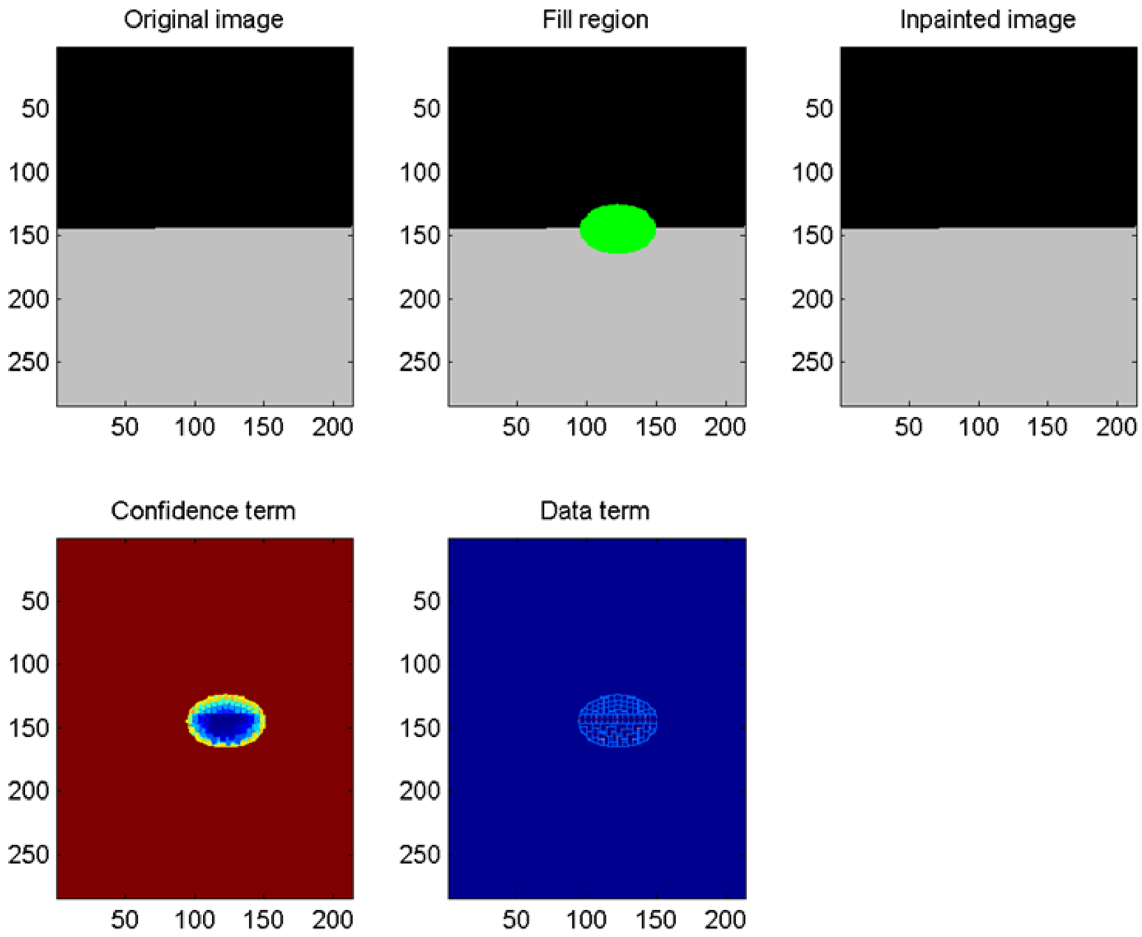
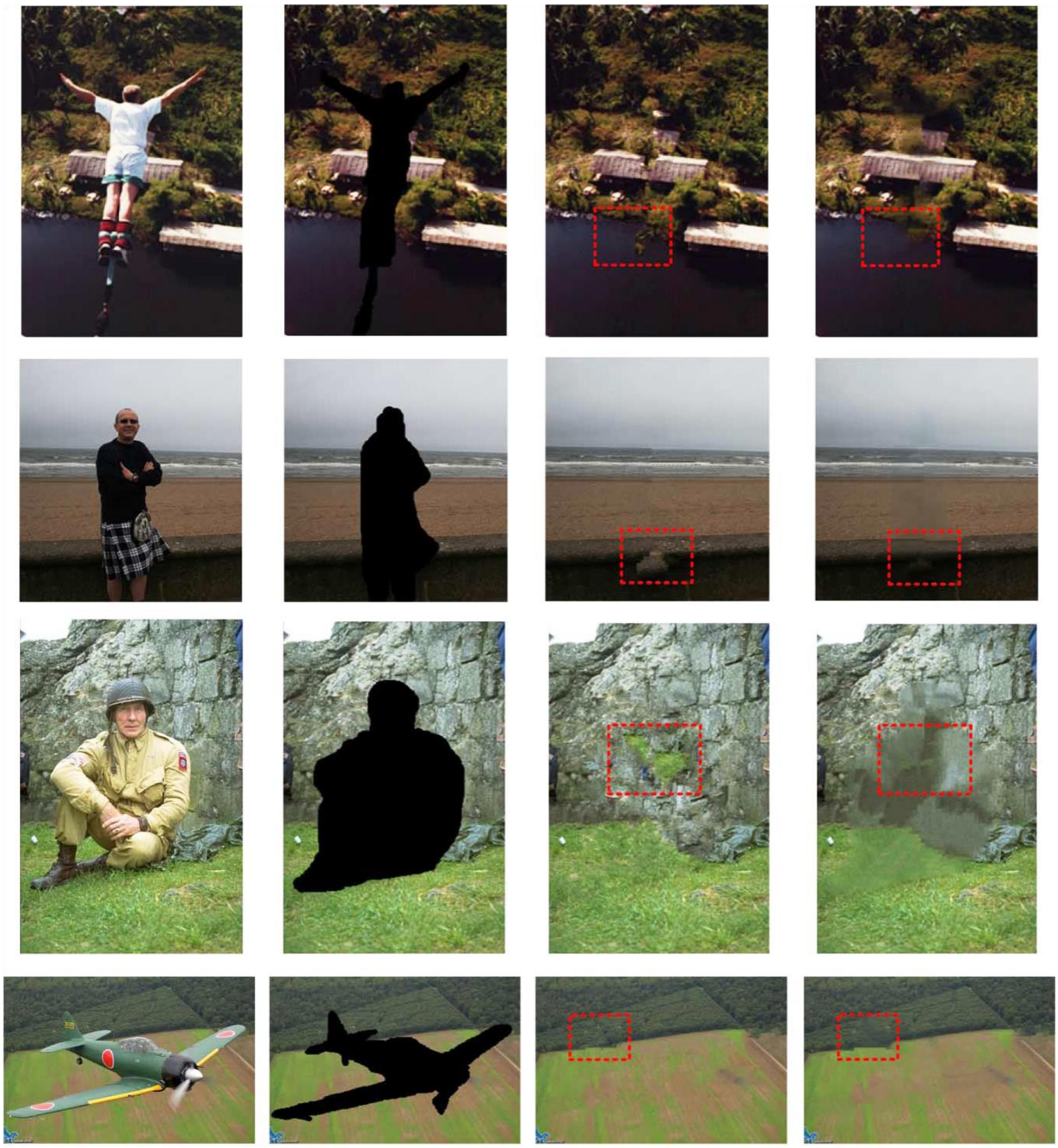


Figure 5.7: Comparison for object removal (a) The original degraded image. (b) The marked image (c) The restored image. (d) The confidence term (e) The data term.



(a) **(b)** **(c)** **(d)**

Figure 5.8: Comparison for object removal (a) Original image (b) Degraded image (c)–(d) The results of Criminisi's examplar-based algorithm [37], Wong's examplar-based algorithm [38], and our examplar-based algorithm.

We now apply the related examplar-based inpainting algorithms. Which are suggested by Criminisi's algorithm [31], Wong's algorithm [38] and the results are simulated in figure 5.8. The first two columns are the posted with the images which are original images and the degraded respectively. The third and forth columns are the results of Criminisi's algorithm [31], and Wong's algorithm [38]. The simulation results which are obtained by Criminisi's algorithm (inpainted patches), are not always consistent with the surrounding textures, the texture of trees occurs in the texture of water as shown in the first row third column, and texture of grass appears in the texture of rock shown in the first row forth column. Although the results obtained by Wong's algorithm, who uses several top best exemplars to infer the unknown patch, are not fair enough but its satisfactorily better than Criminisi's algorithm. But the results have less effect of patch inconsistency. However, it introduces smooth effect as shown in the results.

CHAPTER 6

CONCLUSION & FUTURE ASPECTS

The work undertaken in this thesis primarily discuss about the Digital Restoration of Mural Damaged Images. The implementation of various restoration techniques of murals is presented. The patch match based inpainting algorithm for scratch or text removal, object removal and missing block completion have been analyzed. The thesis analyses and simulated results are obtained for the coherent texture synthesis technique, exemplar inpainting algorithm, and patch sparsity based algorithm.

6.1 Achievement of the thesis

This thesis presented a pixel to pixel and patch propagation based inpainting algorithm for scratch or text removal, object removal and missing block completion. The main factor of this work is that two types of patch sparsity were discussed and introduced into the exemplar-based inpainting algorithm. This was seen from the recent progress of the research in the fields of image sparse representation and natural image statistics.

Our approach employs an exemplar-based texture synthesis technique modulated by a unified scheme for determining the *fill order* of the target region. Pixels maintain a confidence value, which together with image isophotes, influence their fill priority.

The technique is capable of propagating two-dimensional texture into the target region with a single, simple algorithm. Comparative experiments show that a simple selection of the fill order is necessary *and* sufficient to handle this task.

The exemplar method performs at least as well as previous techniques designed for the restoration of *small* scratches, and, in instances in which *larger* objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency.

Now, proceeding towards another technique which is structure sparsity and which was designed by measuring the sparseness of the patch similarities in the local neighborhood. The patch with larger structure sparsity, which is generally located at the structure, tends to be selected for further inpainting with higher priority. On the other hand, the patch sparse representation was proposed to synthesize the selected patch by the sparsest linear combination of candidate patches under the local consistency constraint. Experiments and comparisons showed that the exemplar-based patch propagation algorithm can better infer the structures and textures of the missing region, and produce sharp inpainting results consistent with the surrounding textures. Moreover, robustness towards changes in shape and topology of the target region has been demonstrated, together with other advantageous properties such as: (i) preservation of edge sharpness, (ii) no dependency on image segmentation and (iii) balanced region filling to avoid over-shooting artifacts.

Also, patch-based filling helps achieve: (i) speed efficiency, (ii) accuracy in the synthesis of texture (less garbage growing), and finally (iii) accurate propagation of linear structures.

6.2 Future Scope

In the future, we will further investigate the sparsity of natural images at multiple scales and orientations, and apply it to the image inpainting, super-resolution and texture synthesis. We are also interested in incorporating the human-labeled structures into our framework in order to recover the totally removed structures.

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