Exemplar-based Colour Image Inpainting: A Fractional Gradient Approach with Improved Confidence Term

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DECLARATION

I, Sehajbir Aujla, hereby proclaim that the work which is being presented in this dissertation, entitled "**Exemplar-based Colour Image Inpainting: A Fractional Gradient Approach with Improved Confidence Term**" for the award of degree of Master of Engineering in Wireless Communication Engineering is an authentic record of my own work carried out under the supervision of Dr. Kulbir Singh (Professor), ECED, Thapar University, Patiala and refers other researcher's work which are duly listed in the reference section.

The matter presented have not been submitted by me in any other University/Institute for the award of any degree.

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It is certified that the above statement made by the student is correct to best of my knowledge and belief.

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ABSTRACT

The reconstruction of visually persuasive image from the scratched or teared images is known as image inpainting. It can also be used for intentionally removing some data from the image which is not required but got captured by accident. This prediction of data in place of removed data is done by various inpainting techniques. But the images recovered must look authentic to the user. Texture synthesis and inpainting is combined in the exemplar based methods to fill the void in image, so that it looks pleasant to viewer's eye.

In exemplar-based technique, two types of terms are used namely confidence term and data term. A new priority function in additive form is used for the calculation of prioritisation of pixels to be inpainted in the target region, with an improved confidence term and a fractional based gradient function is used for defining the data term which is more efficient, instead of traditional multiplicative form because the latter causes the priority value to decline rapidly and resulting in inefficient filling of patches.

The proposed algorithm is tested by removing text written on real world images and removing a certain object from the image so that resultant image looks authentic and results are found to be better and more efficient than the present traditional techniques in terms of performance metrics MSE, PSNR and SSIM. From Criminisi Algorithm, there is an increase of PSNR ranging from 0.24 dB to 7.90 dB and from Chandersekran method, increase of 0.1 dB to 0.96 dB is achieved. Also the final image looks more legitimate to the human eye as it should not appear to be tempered with.

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LIST OF ABBREVIATIONS

AIEI	Along Isophote Exemplar-based Inpainting
ANN	Approximate Nearest Neighbour
CIEI	Cross Isophote Exemplar-based Inpainting
DCT	Discrete Cosine Transform
JPEG	Joint Photographic Evolution Group
MSE	Mean Square Error
PDE	Partial Differential Equations
PSNR	Peak Signal-to-Noise Ratio
SSIM	Structural Similarity Index Measure

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Chapter-1

Introduction

1.1 Preamble

Inpainting is process of restoring lost and deteriorated images and videos. In the digital world, inpainting is application of algorithms that remove little defects or substitutes the lost or deteriorated portions of the image especially the smaller ones [1]. It is first used in image processing by Bertalmio et al [2]. Its applications include recovery of deteriorated photographs and removal of certain objects from paintings. It is used in removal of the cracks or patch in image. It is the profession of reclaiming the original images from the images which become inadequate because of different reasons like age deterioration, loss of part of image due to ripping and missing details caused by blockage in front of camera while taking it. Thus, such missing image information must be predicted without introducing inadmissible artifacts which would cause image to look absurd. The inpainted image should look authentic to the viewer such that it should not have any trace of tampering [3].

Figure 1.1 Painting restored by J. Suvee (Louvre) [3]

Problems get even more complex when the inpainting domain is in colour. There are various sequence of events where inpainting proves to be useful. The one such events is case of increasing computing power and availability of large chunks of memory which have discovered new opportunities for working in image and video inpainting. Photographs belonging to ancient era which are bared by exposure to sunlight can be protected, if digitally stored. Old cinema movies gets impaired further when displayed each time, so their digitization can be done and get protected. Common type of harms caused to photographs are scratches or smudges. Due to these defects, certain areas are created causing the authentic image pixels to get missed. There is a possibility of manually restoring these images but that consumes a lot of time. Therefore it is desirable to automate this process. In such situations, there is a need to predict the missing image information without introducing undesirable artifacts. So a number of innovative improvements have been introduced in deciding priority order of patch filling and correlated metrics for the measurement of structure and colour.

1.2 Inpainting

The complete image domain is represented by Ω , which is generally a rectangular area of PC, or a finite Lipschitz domain in R^2. Occlusion of objects in images results in a sub-portion D of Ω having missing data of the images.

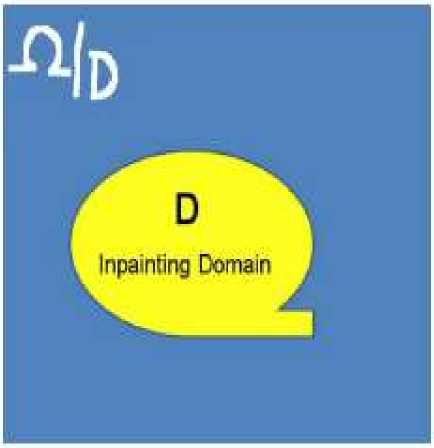


Figure 1.2 Inpainting Problem

1.2.1 Guidelines for Inpainting

A few attainable guidelines concerning the relevant question of how inpainting of an image should be done to look authentic and complete to the visual system of humans. Here the work of famous psychologist Gaetano Kanizsa would be very helpful. In his book [4], different arrangements of plain geometric figure such as polygons and circles partially incomplete and overlapping are discussed. Several persons participated in the test conducted by him for completing incomplete images, it was concluded that a higher percentage of people gives preference to some common principles. Following three guidelines are susceptible for problem solving process [4]:

- The lines frequently or unexpectedly changes their direction are less preferred over those which are straight or curved in nature. This is called the principle of continuation of direction.

- Line forming closed shapes, as they are easy to complete, are preferred over the lines leaving open gaps, which is termed as completeness and closing principle.
- Tendency to convexity: convex shape are preferred over concave ones.

Though these principles are derived from obvious similar figures but these can applied to real world images as edges represent the strongest visual impressions in any image. Images are considered as a collection of objects which are considered homogeneous regions disconnected by edges. This point of view gives rise to the following situations, depending on the size and the position of the inpainting domain, i.e., the area of an image where new contents have to be created [5]:

- The inpainting domain is entirely contained in single textural area or patch: then the inpainting domain can be filled with the neighbouring pixels as they look identical.
- The inpainting domain covers parts of two different textural areas or patches, that is, it contains an object boundary crossing through it: then finding the acceptable course of boundary is the main obstacle. Kanizsa's principles should be taken care of while deciding the boundary.
- The inpainting domain covers more than two objects: if two or more textural regions are overlapping each other, then the inpainting domain contains T-junction. Otherwise this problem reduces to the two-object inpainting problem.

An effective algorithm should be able to successfully grasp all the three conditions simultaneously. Inpainting domain is considered to be association or disarranged blend of simply connected regions. Another desired quality of an excellent patch filling algorithm is that it should not allow the artifacts to over-shoot or grow indefinitely when edges are allowed to grow in a continuous manner [6].

1.3 Flow Diagram of Inpainting for Re-construction of images

Figure 1.3 shows the basic flow diagram of an inpainting problem. First, an image is selected whose damaged area is to be reconstructed or an image from whom user intentionally want to remove some object. Then in second step, masking of the respective damaged area/object to be removed is done manually using paint software. This damaged area/object is called target region and the rest of the image area is known as source region. Then the respective algorithm for removal of selected region is performed. After each iteration of the algorithm size of the mask reduces as some part of it gets inpainted with the pixels selected from the source region and checked whether the image is completed or not. If no, the next iteration proceeds till the completion of the final image [7].

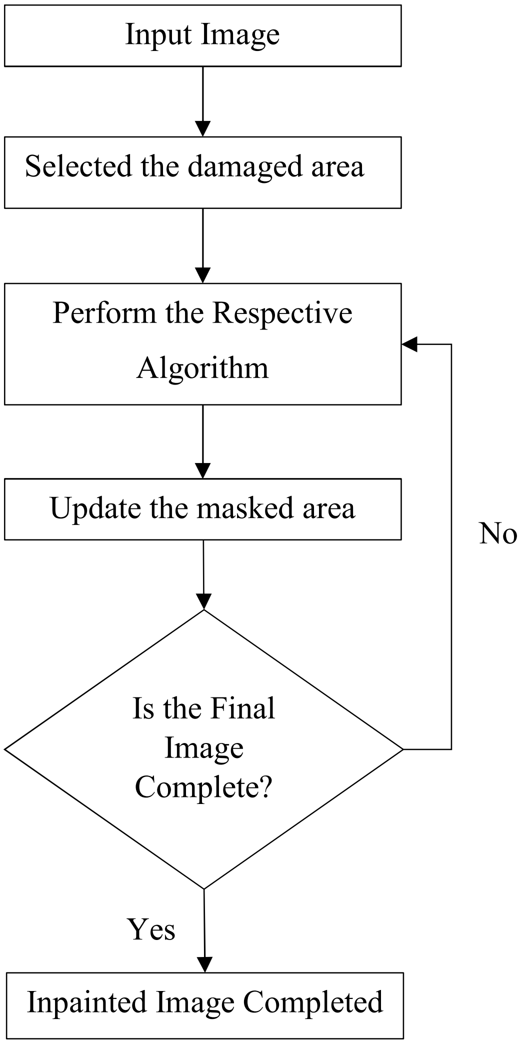


Figure 1.3 Basic Flow Diagram of Inpainting Problem

1.4 Different Existing Methods of Inpainting

A number of inpainting techniques proposed in the past can generally be divided into four categories [7, 8]:

- Statistical-based approaches.
- Variational or PDE-based methods.
- Fragment or exemplar-based methods.
- Hybrid approaches.

In statistical-based approaches, certain random fields are used for drawing the samples used for the inpainting process. These random field can also be determined with the help of techniques like non-parametric estimation and filtering from image database on the basis of maximum entropy principle [9]. Classic models uses the principle of finding the local restraints on energy in gibbs area defined in statistical mechanics, in the same way as that of Ising crystals [10].

In PDE-based methods extrapolation of neighbouring pixels is done for the purpose of predicting the missing information by using criteria similar to the restoration of edges, or variational principles. The inpainting region is assumed to be coherent with adjacent regions through topology preservation. The local neighbourhood modelled by PDEs are diffused with image intensity value for attaining the goal of inpainting. These local methods perform well in case of small regions but cause blurring effect for larger holes. PDE based approaches succeed in inpainting of thin edges but fails in synthesizing the texture accurately [11, 12].

Texture synthesis algorithms uses the sample textures for generating the large image regions. This algorithm mainly focusses on single pixel value at a time and decide its value by searching for similar area in the accessible image data. The fragment or exemplar-based algorithms can be treated as generalized texture synthesis. A complete block is assigned to the inpainting domain for the smooth connection with the neighbouring texture instead of copying single pixels which don't give admissible results. Available image content that can be duplicated plays a prominent role in efficiency of fragment based inpainting algorithms than in pixel based texture synthesis algorithms. If samples of legitimate inpainting fragments are not available in the given image, it can be major problem as new image content can't be generated [13, 14].

Exemplar-based methods are a combination of texture synthesis and inpainting. The main aim is to fill the void in the image in a way that it looks pleasant to viewer's eye. Earlier, two classes of algorithms has been used for solving this problem namely texture synthesis algorithms and inpainting techniques. The former algorithm generates the large image regions from the available sample textures and works well for two dimensional patterns where texture needs to be repeated with little stochasticity, the latter algorithm fills the smaller gaps and works well on one dimensional patterns called linear structures such as lines and objects contours [3].

Hybrid approach is combination of two types of algorithms such as PDE and texture or fragment based synthesis techniques. One algorithm works on extrapolating image data into the inpainting domain in a reasonable way and other one do the task of searching the correct regions in the given image database that could be copied into the inpainting domain. Both of these algorithms have their advantages and flaws.

1.5 Fractional Derivative

The concept of differentiation and integration of non-integer order is no means new. This goes back to Leibnitz note in his letter to L'Hospital dated 30 September 1695 in which the meaning of derivative of order one half is discussed. Subsequently systematic studies and contributions have been made by a number of famous mathematicians including Liouville, Riemann, Holmgren, Euler, Lagrange, etc. Fractional calculus refers to the theory of integrals and derivatives of arbitrary order which generalize and unify the concepts of integer-order differentiation and integration. The Grunwald–Letnikov derivative [15] of an integer order n and the r fold integral of the continuous derivative $f(t)$ are particular cases of the general expression

$$D_t^r f(t) = \lim_{\substack{h\to 0 \\ nh=t-a}} h^{-r} \sum_{m=0}^{n} (-1)^m \binom{r}{m} f(t-mh) \tag{1.1}$$

The above equation triggers the idea of a generalization of the notions of differentiation and integration.

The fractional gradient approach has been used by Chandrasekaran [3] in the field of inpainting. Method presented distinct gradient function and generalized it via fractional derivative for the evaluation of the priority order for filling desired pixels. Two different areas of image could have same mean and in case of application of normal gradient on the image, it will be difficult to differentiate between the pixel distributions that makes decision regarding which patch should be given more priority crucial challenge. So the sole guiding parameter for prioritization of filling order chosen is local gradient at the pixel p on the boundary of the desired area as normal gradient based functions illustrates degrading performance in the presence of noise in a specified image, gradient function is replaced by generalized fractional order derivative.

1.6 Motivation of the Dissertation

The main motivation of this dissertation is to develop a method that provides reconstruction of images with minimum errors, better perceptual and quantitative analysis of output image. It employs exemplar based method for deciding the priority order for filling missing/damaged image pixels using fractional gradient. Fractional gradient provides the fractional order, which is prominent in case of noisy images, for better detection of true edges rather than noisy edges.

1.7 Organisation of the Dissertation

This dissertation is organised in the form of chapters as illustrated below:

Chapter 2: Literature Review, A Study is done regarding various present methods of texture synthesis, structure propagation and other techniques used for the purpose of image inpainting are discussed.

Chapter 3: Exemplar Based Inpainting Done Using Improved Confidence Term, novel algorithm in case of inpainting are discussed. The effect of confidence and data term essential for deciding the priority function is explained. The details of the algorithm used for the inpainting process is provided in detail.

Chapter 4: Results and Discussions, Results using various synthetic images, images with known ground truth data, and images without known ground truth data are shown. Also comparison of used method with other existing methods is done with qualitative parameters such MSE, PSNR, and SSIM.

Chapter 5: Conclusion and Future Scope, The work done in this dissertation is concluded in this chapter and scope is also discussed for the future research.

Chapter-2

Literature Review

2.1 Introduction

This chapter overviews the methods and work presented by various researchers in the domain of inpainting. Papers presented discusses different techniques such texture synthesis, exemplar based, hybrid algorithms. It also includes the work done in the field of fractional derivatives.

2.2 Literature Review

Patel *et al.* [1] presented a survey paper in which they explained about the process of image inpainting done manually by painters for removing the cracks and defects present in the picture. But with the digitization of this field, missing information can be retrieved with the help of various inpainting techniques using information surrounding a pixel. In this paper different present techniques like texture based, exemplar and search based, PDE based and hybrid have been analysed and examined for image inpainting. A brief overview of algorithms for video inpainting have also been given which could guide novice researchers to pursue this field.

Chandrasekaran *et al.* [3] proposed a quick and smooth technique based on a distinct gradient function and generalized it via fractional derivative for the evaluation of the priority order for filling desired pixels. Of all the present advances in field of exemplar-based methods quoted in the literature, their results were found to be more robust and superior in terms of qualitative metrics and more soothing (having less errors) for eyes of the perceiving user. Sole guiding parameter for prioritization of filling order chosen was local gradient at the pixel p on the boundary of the desired area. As normal gradient based functions illustrates degrading performance in the presence of noise in the specified image, gradient function was replaced by proposed generalized fractional order derivative.

Criminisi *et al.* [6] discussed the texture synthesis algorithm used for synthesizing large image regions and inpainting techniques for filling in smaller gaps. They proposed a novel and efficient algorithm that united the advantages of these two approaches. They studied the necessary process of exemplar based texture synthesis needed to reproduce both structure and texture. Order of filling the missing image pixels highly determines the accomplishment of the structure propagation. A best-first algorithm was proposed which propagated the synthesized pixel values confidence style identical to the information propagation in inpainting. The robustness and efficiency of algorithm was demonstrated by removing different obstructing objects as well as thin scratches from manually selected real and synthetic images.

Efros *et al.* [14] proposed a method for texture synthesis on depending on a non-parametric estimation process. A new image was created in an outward manner from an initial seed, that is, one pixel at a time in this texture synthesis process. Conditional distribution of a pixel, provided all its neighbours are already synthesised and assuming a Markov random field, was estimated by checking the given sample image and concluding all its neighbouring pixels. A single perceptually intuitive parameter was used to control the degree of randomness. Local parameters was sustained as much as possible for producing satisfying results for a broad range of synthetic and real world textural images. The resulting algorithm performed well on wide range of textures and specifically for constrained synthesis problem (hole-filling).

Wu *et al.* [16] discussed method of exemplar-based inpainting. The data term used in the algorithm is the deciding factor for preserving the linear structure. In this paper, broad mathematical analysis of Along Isophotes Exemplar-based Inpainting (AIEI) and anisotropic diffusion is done and it is been proven that data term is sole factor deciding strength of isophotes. As a result a novel method of Cross Isophote Exemplar-based Inpainting (CIEI) is proposed which conclude the data term to the cross direction, that is, to the perpendicular of normal isophote. CIEI has superior linear structure preserving property as its data term considers the thickness of the edge. Theoretical analysis and experiments performed certifies the model.

Chen *et al.* [17] depicted the process of extensively used inpainting for restoring the damaged photographs and pictures or removing the damaged portion/unwanted objects in an image. They discussed about Criminisi's algorithm of exemplar-based inpainting which combined the process of PDE based inpainting and texture synthesis showed enormous efficiency for removal of large objects. But since that approach had certain drawbacks such as high time for completion of image and bad visual perception, they enhanced Criminisi's exemplar based algorithm on the basis of searching process and transferring colour to the target patch. This method was also applicable to all other exemplar-based methods as demonstrated by experimental results performance.

Kwok *et al.* [18] presented a novel algorithm for achieving associated response and generation of desirable results in field of exemplar-based image inpainting. Authors modified the exemplar based method by incorporating DCT for matching the exemplar patches in the image. They figured out the matching scores with lesser coefficients by decomposing exemplars by DCT which is remarkable step in research of image inpainting. The logic behind the use of fewer coefficients is that the effectiveness of Approximate Nearest Neighbour search algorithm drops incomparably while using higher dimensions. A local gradient-based filling algorithm was also developed for the completion of image blocks with uncertain pixels to accelerate the process of matching by adopting ANN search without breaking the continuum of the image. The effectiveness of the method was shown by experimental results.

Driori *et al.* [19] presented a unique method for regeneration of missing image information in an image caused by wearing and tearing during course of time. Synthesis process resulted in fully visually plausible and coherent image by getting data from foreground and background components of an image. For the assuming the unknown parts, training set was made with the help of already visible pixels. An iterative approximation of the unknown region was done and mixing process of adaptive image fragments was performed. Confidence map was constructed using values of inverse matte and for the goal of traversing incremental values from high confidence to low, a level was set up. Image fragment with maximum similarity was selected by fast smooth approximation during each step of the algorithm. With the increase in mean confidence of the selected fragments because of their composited nature, the likelihood of getting complete inpainted image also increased. The results were validated by completing different photographs and painting.

Shen *et al.* [20] removed meaningful objects with the help of an innovative gradient-based image completion algorithm from natural images and photographs. Their algorithm completed the removal process in two steps. Firstly, a patch based filling algorithm was used to finish calculation process of gradient maps in the removal area of image. Then Poisson equation was solved for restoration of the image from gradient maps. Gradient and colour information are assimilated in this new criterion for developing a new patch making approach for guiding the completion of gradient maps to get the better image completion results. The work done in this gradient based image completion approach was demonstrated by comparing the achieved results with other existing techniques.

Bugeau *et al.* [21] presented a unifying variational model by bringing together three different basic algorithms specifically geometric PDE, copy and paste texture based synthesis and coherence between neighbouring pixels and provided an algorithm based on exemplar based inpainting for approximating the proposed energy functional minimum value. The energy proposed by authors consisted of three different terms justifying the above mentioned algorithms. The first term presented variational formulation of texture synthesis. The second and third terms are the combination of ideas of diffusion and coherence applied in the patch space. Multi-resolution scheme was used for purpose of computing the weights for patch selection and required post processing step namely Poisson editing.

Zhou *et al.* [22] stated a patch based target region (unknown) filling process which was based on the process of best matching the patches present in the source region of the image in multiple iterations. The patch size was chosen to be default number or kept fixed. It could also be made inversely proportional to the spatial frequency of the specified image. Patch size determined the final accuracy of the image by deciding local characteristics of the source image on the basis of how correctly it selected the desired patch. A new method for improving the performance was given in this paper by computing relevant patch sizes for completion of the image. This process was considered as an optimization step for determining the patch size that could minimize the involvement of image gradients and homogeneous features of image.

Nishihara *et al.* [23] presented a simple unique patch shifting scheme based on exemplar-based image inpainting. Conventionally in different exemplar-based techniques, the number of known and unknown pixels in the target patch were not considered. When large unknown areas were conferred with smaller number of known pixels that often caused errors to occur. So the authors proposed new patch shifting algorithm which provided more valid target patch approach than conventional methods. In this approach, a predefined threshold of known pixel value was used, which if not attained, the target patch would be shifted in the increasing known pixel value direction to overcome the previously defined problem. This had increased the likelihood of filling in each patch more accurately.

Sarpate *et al.* [24] proposed an algorithm for filling the hole left behind in an indistinguishable form after synthesis of the structure and texture of an image. Exemplar-based texture synthesis and region filling method was used as an experiment for computing the definite value of colours present. The estimation efficiency and performance of the proposed algorithm in terms of inpainting visual quality was illustrated with the application on number of different real and satellite images by removing obstructing objects.

Grossaur [25] treated specific regions of an image independently by combining two different approaches, PDE based inpainting and texture synthesis approach for inpainting. This led to the use of a segmentation step as an advanced aspect which assured the appropriate choice of texture samples for the synthesis process. A unique concept of local texture synthesis was proposed which even in large domain problems provided adequate results in the presence of complicated environment.

Bertalmio *et al.* [26] presented an algorithm which contained the concept of disintegrating an image into the sum of two different key components containing two separate functions and then texture filling and structure algorithms was used for regeneration of each of these functions independently. The missing image information region was filled simultaneously with these texture and structure filling functions. The basic image structure in disintegration was represented by the first function which is bounded variation and texture and noise presence was captured by second function. Image inpainting algorithms was used for recovering the missing pixel content in bounded variation image, while texture synthesis techniques were used for reconstruction of the same area in the texture image. The sum of these two images conclude the final reconstructed image. The proposed image decomposition process technique merged the three previously defined components for allowing the simultaneous use of these different methods for filling in missing image characteristics in an image.

Rane *et al.* [27] showed that compression algorithms such as JPEG would be used for filling of missing data block in case of wireless transmission of an image. Firstly, images would be segregated into blocks of 8×8 pixel block size. The whole block of the image could be ruined by noise, when such images have to be transmitted over fading channel. The lost data between last transmitted block and its neighbours could be regenerated using correlation function instead of typical retransmission protocols. Reconstruction of structure and texture in the lost block could be done using image inpainting technique and textured block method respectively. Depending upon availability of the adjacent blocks switching could be done between two techniques in an automated manner. The operational capability of this method was checked in as association with lossy images and various images with missing blocks were tested for getting the performance results of above method.

Vese *et al.* [28] dedicated this paper for designing partial differential equations and functional minimization for application on real textured images. They broke down the given image f, possibly a texture image, into the combination of two different functions u and v. The first function $u \in av$ represent bounded variation such as sketchy approximation of f and latter function meant for texture and noise present in original image. For the objective of designing function v, they used the space of oscillating functions, which represent the dual nature of bv space introduced by earlier researchers. The newly developed algorithm making the usage of differential equations can be quickly solved thus making it simpler and effective in practical aspects. Finite differences method was used for implementation and different numerical results were drawn showing the attained separation $(u + v)$. Finally conclusion was made about getting the aid of this method in texture separation and texture segmentation processes.

Xu *et al.* [29] proposed two unique concepts of patch level sparsity for deciding parch priority and patch representation introducing a novel exemplar based inpainting algorithm by inspection of sparsity in natural images. These steps are crucial in propagating patches in exemplar based inpainting approach. The confidence of a patch based on image structure is measured by designing patch structure sparsity for checking the sparseness of its positive similarities with its adjacent pixels. For the inpainting purpose, priority was directly proportional to the structure sparsity, hence larger structure sparsity, higher will be the priority assigned to the patch. An assumption was made that patch which was to be filled could be characterized by the sparse linear combination of present candidate patches in a restricted scheme of local patch consistency. Structure sparsity performs better for the separation of structure and texture than the conventionally present exemplar based approaches and the freshly inpainted regions was found to be sharp and consistent with the encircling textures.

Yamauchi *et al.* [30] explained a simple method for preserving real life photographs that have been digitized. This attributes for the removal of annoying objects present such as logos, wires, subtitles and elimination of image defects like scratches and stained developed over period of time or caused by negligence of some person. The proposed method results were very much promising as restored images look acceptable and surprisingly authentic in some cases. A multiresolution approach combining the effects of image inpainting and texture synthesis demonstrated pleasing results for getting rid of defects present in wide variety of images and overcoming the limitations of individual approaches.

Bhaskar *et al.* [31] described various inpainting techniques, in their survey report, as nothing but a simple process for removal of unwanted objects from real world images without making it look absurd and filling the removed area with information present in the rest of the image.

Research shows that a lot of work have been done in field to retrieve the damaged image areas successfully. They have proposed a novel method for the reconstruction of videos from their damaged counterparts. It was achieved by applying exemplar based image inpainting technique for filling the missing parts of the videos. Firstly the damaged image frames were extracted from the videos and obstacles were removed using exemplar based techniques. This paper mainly deals with explanation of various methods used for reconstruction of missing places in video as reconstruction of damaged images and videos would be helpful for preserving data in digital form.

Rane *et al.* [32] proposed a method for interpolation of lost image blocks when transmission was done through wireless media, with help of wavelet-domain technique. Congestion in the packet switched networks and wireless channels fading nature would be responsible for misplacement of block code images in wireless transmission. Correlation function between lost block and its neighbours was used for regeneration of block in wavelet domain rather than transmitting the query protocols again. Presence of edges in the lost block was determined by a smooth thresholding algorithm. The minimization of blocking effect was completed by designing an interpolation scheme without causing any harm to the edges or texture in the interior of the block. The squared error between border coefficients of block its neighbours was minimizes with the help of above designed interpolation scheme at each transformation scale. The low estimation overheads and its comparison with other reconstruction schemes were examined by the performing the algorithm of various present test images.

Sun *et al.* [33] defined structure propagation as a global optimization problem by imposing structure and consistency limitations and synthesised patches in the unidentified region along the curves specified by the user manually using patches chosen over the curves in the known region of the image. Dynamic programming was used for determining structure propagation in case of single specified curve. Patch based texture synthesis was used for filling of unknown regions after accomplishing structure propagation. This approach performed well on numerous real world examples which are difficult for present state-of-the-techniques.

Sarode *et al.* [34] presented an algorithm which further develop the previously proposed algorithm of examining the whole image. Considering the fact that most of the significant information lies in the neighbouring pixels, search process was reduced by seeking the nearby pixels only thus greatly reducing the time to complete the inpainting task. This technique was primarily used for removal of cracks and objects from the image.

Wei *et al.* [35] presented an algorithm for random generation of samples in a texture synthesis based search method in which resulting texture remained identical. For this objective, a pyramidal representation was created of each level serving as a fixed number of neighbouring pixels on which each texture sample depends. The lowest level, that is, bottom level of the pyramid was inherited by noisy image, which was predetermined and smaller in value. Whenever renderer requested a sample, the generation of corresponding dependent samples were done at once, which assisted in generating samples in any random order. The proposed pyramidal archive (cache) accumulated the texture samples and their dependents to make the algorithm efficient. Despite the expensive generation of first few sample, there is considerable reuse making samples cost less. Most rendering algorithms showed good coherence, so there is a high possibility of cache reuse.

Yadong *et al.* [36] recovered the missing parts created by the elimination of foreground or background elements from an image of real world scenario with the proposed fast and adaptive method. They synthesised the missing information by patches drawn from the areas which are located horizontally in the image contrasting to the regular broad search used previous texture synthesis based approaches to find appropriate textures. This particular method was used because of the strongly horizontally oriented natural pictures and an adaptive method for determining the template size for grabbing features of different scales in image was presented.

Chandrasekaran *et al.* [37] have done the pre-processing of digital images by using the fractional derivative based techniques. For the purpose of image contrast enhancement fractional derivative mask based on the Grunwald-Letnikov derivative approach was proposed in this paper. The proposed mask could enhance image in various directions in one step as it was of multidirectional nature. Training image set was used for learning process of regularisation based prediction network whose statistics were used for deciding the final fractional order. Relative to the desired improvement in blur reduction process, fractional order was predicted in a controlled way for reducing the blurredness. The efficiency of the proposed novel filter was calculated by performing experimental analysis and comparing blur metrics on a wide range of real world images.

Garg *et al.* [38] presented a paper which showed that for the identification purpose of regions or objects in an image, critical role is played by texture of that image. A two-dimensional fractional differential operator was used, for the enhancement of textural information and overcoming the constraints of classical derivative operators, which is an improved version of Grunwald-Letnikov based fractional derivative. Different texture enriched digital images was tested by appliance of this nonlinear filter mask and intensity factor was varied to control the enhancement of features of images. Information entropy and average gradient are the parameters used for quantitatively analysing the enhancement process on an image. The proposed enhanced version provided better results in terms of information entropy which was improved by the value of 0.5.

Zhuzhong *et al.* [39] constructed fractional differential operators for use in place on integral order derivatives. By making fractional differential order of the value 1 or 2, first or second order differentials can be exercised, indicating that the integral order differentials are special cases of fractional differential. A higher signal to noise ratio was achieved in case of image edge detection experiments based on fractional differential operator as compared to conventional first and second order differential operators.

Ortigueira *et al.* [40] discussed that no matter how much advancement appeared in the theory and application field of fractional calculus, some of the methods continued to remain confusing making their use less efficient and difficult. The use of fractional differintegration from practical point of view considering both conventional (global) and Grunwald-Letnikov (local) definitions was studied in this paper. As Cauchy formulation is coherent with conventional practices, it must be accepted in field of signal processing and control applications.

A broad range of approaches have been presented in the literature, which describes the different inpainting techniques. These techniques can be classified into statistical, partial difference equations, fragment based and hybrid.

2.3 Evaluation Parameters

The Qualitative analysis of the algorithm is done on the basis of three parameters, namely MSE, PSNR and SSIM. The average of the difference between the original image and image obtained after applying the inpainting algorithm or the MSE is defined as difference between pixel values predicted and pixels originally present in the undistorted image. It can be obtained by

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{2.1}$$

where, $M \times N$ is the size of the image. $I(i,j)$ is the reconstructed image and $K(i,j)$ is the original image. The minimum is the value of MSE, better is the final image. PSNR can be defined as difference between the processed image and the original image. It is represented in dB scale and can be obtained by using the formula:

$$PSNR = 10 \log_{10} \left(\frac{R^2}{MSE} \right) \tag{2.2}$$

where, R is the maximum value of the pixel in an input image (here 255, as the images are represented as 8-bit representation). Higher the value of PSNR, better is the resultant image. SSIM is used to measure the similarity between the two images. It is considered better than the previous two metrics because it takes image deterioration as change in structural quality rather than taking absolute errors as in former cases.

2.4 Gaps in Study

Based on the analysis of the techniques discussed in the literature survey, following gaps have been identified.

- Data term used for prioritization of the pixels to be filled plays a pivotal role. For this purpose some methods does require a dot product computation between the normal to the inpainting boundary and the isophotes but the patch filling priority order could be incorrect on account of varying shapes of the boundary and their associated normals.
- Secondly, confidence term used in case of exemplar based inpainting techniques depends upon the neighbourhood of the target pixel. Hence it is considered to be most important factor for inpainting task as higher number of present adjacent pixels provides greater priority to the reference pixel. But this has not been given much preference in the literature.
- As two different distributions can be centered on the same mean, so averaging operation used in average gradient function would lose its differentiating strength to decide the location of inpainting. Hence, generalization could be done with fractional differential methods.

2.5 Objectives of Dissertation

On the basis of literature review of existing inpainting techniques and identifying gaps, following are the objectives:

- To study and analyse different existing techniques of image inpainting.

- To improve the performance of exemplar-based inpainting using fractional derivative and confidence term.
- Comparative analysis of the proposed algorithms with existing techniques.

2.6 Methodology

Several techniques are available in literature for image inpainting of various synthetic and real world images. Exemplar based technique is found to be better than the rest of techniques. Confidence term used in exemplar-based techniques plays an important role as it gives us the idea of already filled pixels in a patch and it drops down rapidly with the increase in number of iterations used, thereby reduces the value of priority function and causing incorrect filling of pixels. So a regularised confidence term is used to cope up with above defined problem. It is used along with fractional approach for deciding the data term used for differentiating textural regions and for removing the intentionally written text on image and eliminating desired object from the image.

2.7 Summary

In this chapter different techniques for image inpainting are discussed. Different techniques like texture synthesis, CIEI, PDE, Exemplar are studied. Literature review for fractional transforms is also done. Evaluation Parameters MSE, PSNR, SSIM used for the purpose of assessment of performance analysis are discussed. At the end, gaps are identified based on the study and objectives are drawn and a methodology for the desire of completing the objectives is discussed.

Chapter-3

Exemplar Based Inpainting Done Using Improved Confidence Term

3.1 Algorithm by Criminisi in exemplar inpainting

Criminisi *et al.* [6] discussed the texture synthesis algorithm used for synthesizing large image regions and inpainting techniques for filling in smaller gaps. They proposed a novel and efficient algorithm that united the advantages of these two approaches. They studied the necessary process of exemplar based texture synthesis needed to reproduce both structure and texture. Order of filling the missing image pixels highly determines the accomplishment of the structure propagation. A best-first algorithm is proposed which propagated the synthesized pixel values confidence style identical to the information propagation in inpainting. The methodology used by Criminisi is presented in brief manner below.

First, given an input image, the user selects a target region Ω, to be removed and filled. The source region Φ, defined as $\Phi = \mathfrak{I} - \Omega$.

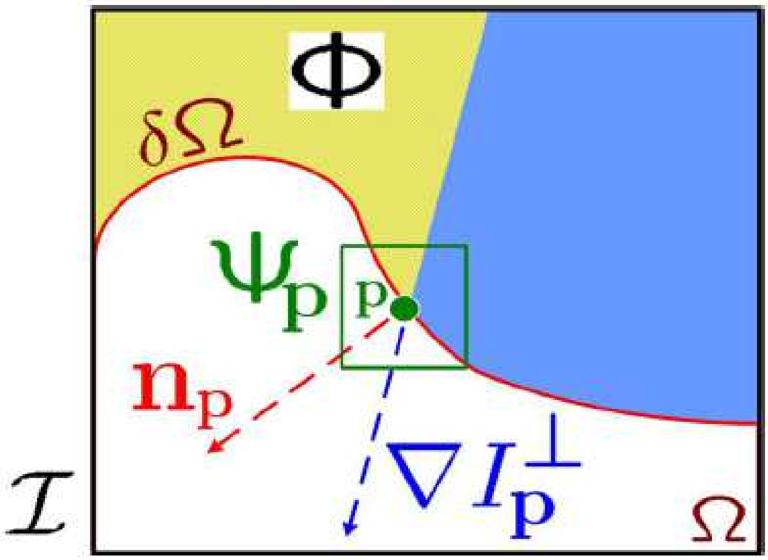


Figure 3.1 Criminisi Inpainting Notation Diagram [7]

Synthesis task is completed by the defined algorithm on bases of the priority function value selected for the patches in the boundary area. The patch having the maximum priority is filled first into the desired target area. The calculation of priority function is partial towards the pixel values lying continuum of edges and are encircled with pixels having more confidence values. Given a patch Ψ_p centred at the point p for some $p\epsilon\delta\Omega$ (see Figure 3.1), they define its priority $P(p)$ as the product of two terms [6]:

$$P(p) = C(p) * D(p) \tag{3.1}$$

$C(p)$ denotes the confidence term and $D(p)$ the data term, and they are defined as follows:

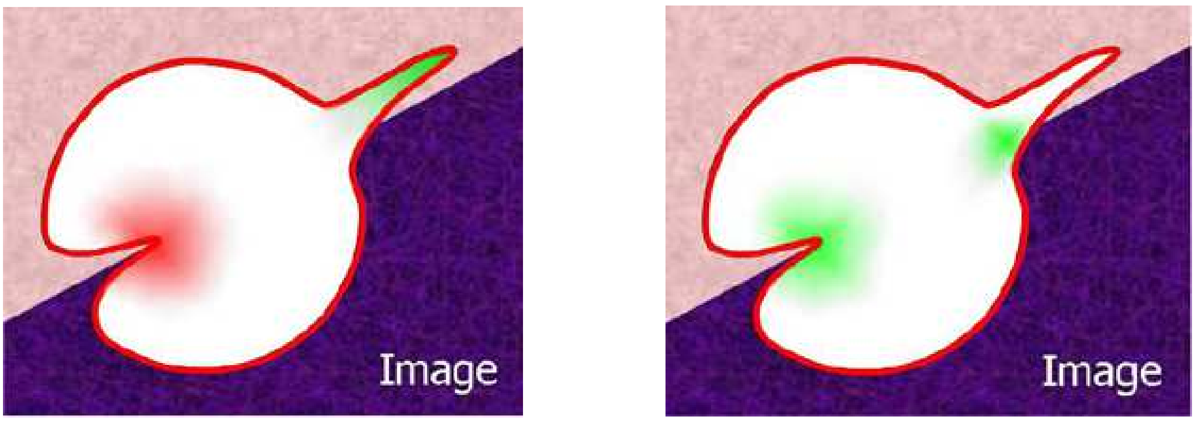
$$C(p) = \frac{\sum_{q\epsilon\Psi_p\cap(\mathfrak{I}-\Omega)} C(q)}{|\Psi_p|} \tag{3.2}$$

$$D(p) = \frac{|\nabla I_p^{\perp}.n_p|}{\alpha} \tag{3.3}$$

where, α is normalisation factor and for grey-level image, it's value is 255.

3.2 Importance of Data Term and Confidence Term

The confidence term assigns high filling priority to out-pointing appendices (in green) and low priority to in-pointing ones (in red), thus trying to achieve a smooth and roughly circular target boundary as shown in Figure 3.2 (a). The data term gives high priority to pixels on the continuation of image structures (in green) and has the effect of favouring in-pointing appendices in the direction of incoming structures described in Figure 3.2 (b). The combination of the two terms produces the desired organic balance between the two effects, where the inwards growth of image structures is enforced with moderation [6].



(a) (b)

Figure 3.2 (a) Effect of Confidence Term, (b) Effect of Data Term [6]

3.3 Algorithm presented by Chandersekran in exemplar inpainting

Chandrasekaran *et al.* [3] proposed a quick and smooth technique based on a distinct gradient function and generalized it via fractional derivative for the evaluation of the priority order for filling desired pixels. Of all the present advances in field of exemplar-based methods quoted in the literature, the results were found to be more efficient and superior in terms of qualitative metrics and more soothing (having less errors) for eyes of the perceiving user. Sole guiding parameter for prioritization of filling order chosen was local gradient at the pixel p on the boundary of the desired area. Therefore the local gradient at the pixel p on the boundary have been intentionally chosen to be the sole guiding parameter for filling order priority. The results of the proposed method have demonstrated superior performance over the previous complex approaches under minimal noise conditions [3]. Having realized the fact that any gradient-based function will exhibit deteriorating performance in the presence of noise, they have generalized the proposed gradient function by replacing it with fractional order derivatives. The standard gradient function is a special case, when the value of fractional order r becomes equal to unity. The change made by authors to the existing Criminisi algorithm is done in terms of data term as follows [3]:

$$D(p) = |\nabla^r u(p)| + \; log(|\nabla^r u(p)|) \tag{3.4}$$

where,

$$|\nabla^r| = \sqrt{\left\{\max\left(\tilde{u}^r_{Fx}, \tilde{u}^r_{Rx,}\right)\right\}^2 + \; \left\{\max\left(\tilde{u}^r_{Fy}, \tilde{u}^r_{Ry,}\right)\right\}^2} \tag{3.5}$$

defined the fractional gradient at the image pixel $p(x, y)$ and,

$$\tilde{u}^r_{F*} = \sum_{R,G,B} u^r_{F*} \, , \tilde{u}^r_{R*} = \sum_{R,G,B} u^r_{R*}$$

where, symbol * represents x or y. Here Δx and Δy are set to unity and,

$$u^r_{Fx}(x, y) = \frac{\partial^r_F u(x,y)}{\partial x} = \frac{1}{(\Delta x)^r} \times \left\{u(x, y) - ru(x + 1, y) + \binom{r}{2} u(x + 2, y) \ldots\right\} \tag{3.6}$$

$u^r_{Fx}(x, y)$ is the right sided (non-causal) discrete domain fractional differentiation function [3] along the x-direction also called forward differencing of u in x-direction

$$u^r_{Rx}(x, y) = \frac{\partial^r_R u(x,y)}{\partial x} = \frac{1}{(\Delta x)^r} \times \left\{u(x, y) - ru(x - 1, y) + \binom{r}{2} u(x - 2, y) \ldots\right\} \tag{3.7}$$

$u_{Rx}^{r}(x, y)$ is the reverse differencing in x-direction and similarly forward differencing u_{FY}^{r} and reverse differencing u_{Ry}^{r} in y-direction can be formulated with value of $r = 0.1$. Whereas, the confidence term was kept same as given by Criminisi [6].

3.4 Algorithm with Improved Confidence Term

The algorithm discovered in [41] defines that the confidence function in Criminisi's algorithm reduces exponentially with a rapid drop to zero as the filling process continues. It makes the values of calculated priority indistinguishable, thus, resulting in incorrect order of filling, priority term's multiplicative form should be replaced due to sensitivity of the numerical multiplication to utmost values resulting in over amplified influences. To evade prescribed deficiency, the actual priority function $P(p)$, defined in multiplicative form needs to be reformulated. From mathematical viewpoint, the response of an additive function is linearly proportional to its input and is more stable to unexpected noise and variations. So an additive solution was adopted for overcoming the above described problem of declining confidence term value. They also proposed that the confidence term in the additive form of priority did not match the order of the data term. Thus confidence term with the regularized version is used. Also, the addition of weights to different components in the definition of priority term is done so that a balance between confidence and data term could be maintained. The approach used is an extension of above explained method with incorporating the enhanced data term used in Chandersekran *et al.* [3]. The changed priority value becomes [41]

$$P(p) = C(p) + D(p) \tag{3.8}$$

The addition of weights to different components in the definition of priority term so that a balance between confidence and data term could be maintained. Thus the modified priority term can now be represented as

$$P(p) = \alpha \times R_c(p) + \beta \times D(p), \quad 0 \leq \alpha, \beta \leq 1 \tag{3.9}$$

where, α and β represent the component weights of confidence and data terms, such that, $\alpha + \beta = 1$ and $R_c(p)$ is the regularized confidence term

$$R_c(p) = (1 - \omega) \times C(p) + \omega, \quad 0 \leq \omega \leq 1 \tag{3.10}$$

where, ω is regularising factor.

The proposed equation formed by mixing the data tern form Chandersekran method and confidence term from [41] is used for the calculation of priority term for deciding the priority of patches to be filled in painting domain becomes:

$$P(p) = \alpha \times ((1-\omega) \times C(p) + \omega) + \beta \times (|\nabla^r u(p)| + log(|\nabla^r u(p)|)) \quad (3.11)$$

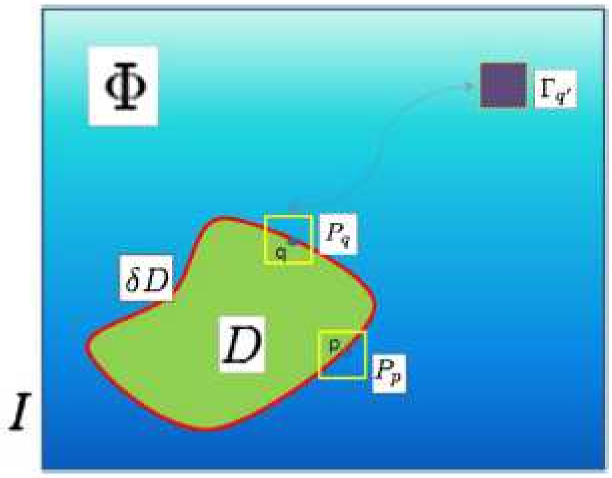


Figure 3.3 Notation Diagram [3]

The algorithm used for the purpose of inpainting is summarized as follows:

Step 1: Inpainting domain or the area to be worked upon is manually selected by user. δD represent the boundary of the selected region. The area D called as target region diminishes as the algorithm proceeds. The source region from where pixel values or patches are be taken to fill the desired area D is given by $\phi = I \backslash D$. The target region decreases with the increase in each step of algorithm.

Step 2: Now for target region, data function defining the fractional derivative's strength is computed as given in (3.4).

Step 3: For all the patch P_p, with p as its center, regularised confidence term with $\omega = 0.7$, is calculated with which defines the number of valid source pixels located in the patch from domain Φ.

Step 4: Then, the priority values $P(p)$ in (3.11) are determined as inpainting of patches along the boundary requires a patch filling order.

Step 5: Now the patch P_q, with the maximum value of priority function $P(p)$ is selected.

Step 6: The best exemplar patch $\Gamma_{q'}$ from the source region is searched that minimizes the function

$$\varphi_q = arg \min_{P_q \epsilon \Phi} d(P_q, \Gamma_{q'}) \quad (3.12)$$

where, distance $d(P_q, \Gamma_{q'})$ describes the sum of squared difference taken between the patch having highest priority value and the patch to be filled in the target region.

Step 7: The relevant patch $\Gamma_{q'}$ found in previous step is copied to corresponding patch P_q, for all the pixels belonging to the intersected area of target region and selected patch ($\forall p \in P_q \cap D$) and the boundary is updated.

Step 8: Until all target area D is completed, above algorithm is repeated depending upon the size of the image and patch.

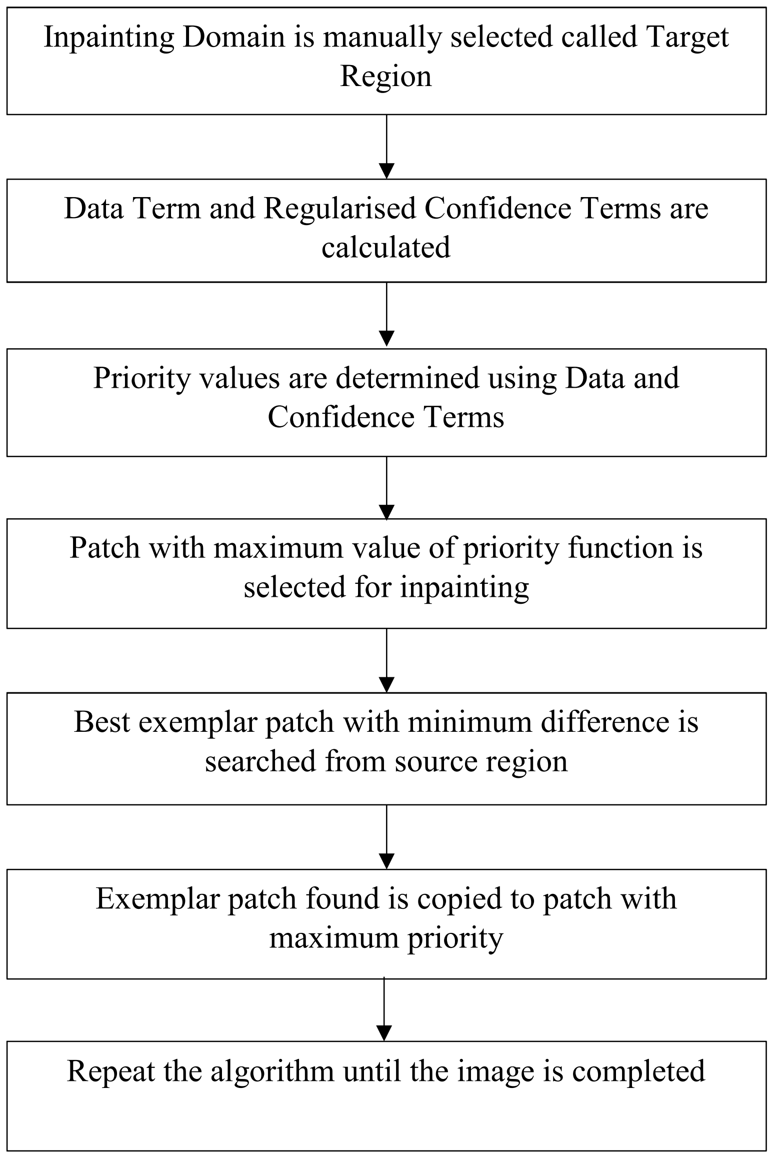


Figure 3.4 Flow Chart of the Proposed Algorithm

3.5 Summary

In this chapter, exemplar-based texture synthesis algorithm by Criminisi is discussed in detail. Priority term used for prioritization of patches to be filled is presented in multiplicative form. Importance of data term and confidence term is explained as they are the main terms responsible for prioritization of patches to be filled in the inpainting domain. The method by Chandersekran is presented that demonstrates the use of fractional derivative in the field of inpainting. The drawbacks of multiplicative form of priority term are explained. The resulting equation modified, using regularised/improved confidence term along with fractional data term, becomes additive in nature rather than multiplicative form of priority term is used and stepwise algorithm for performing the inpainting task is discussed in detail.

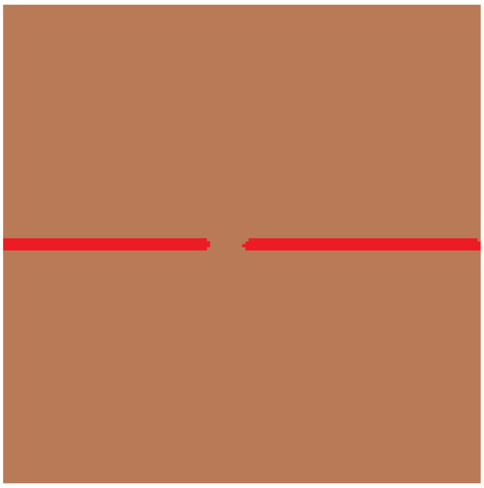
Chapter-4

Results and Discussions

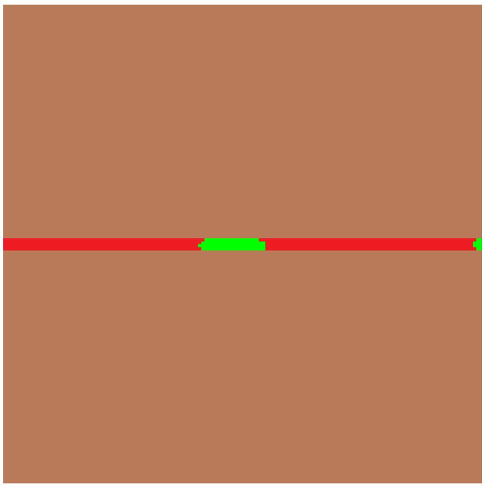
The presented scheme is evaluated by considering the various images such as synthetic images and images with known and unknown ground truth data of different sizes for the goal of filling in the missing information or removing the unwanted data which are available in database given in [42, 43]. The synthetic images are used for checking the proposed algorithm that whether it reconstructs the simple objects such lines efficiently or not. Images with known ground truth represents the real world images which get deteriorated. With passage of time, some important documents get scratched or being mistakenly written on could be restored. Various images like Baboon image (512×512), Bungee Jumper image (308×206), Cat image (133×490), Jeep image (254×381) and other images of different sizes with text written and scratches on them are taken for the purpose of removing corresponding unwanted material. The efficiency of the algorithm is depicted in form of parameters MSE, PSNR, SSIM. Sometimes, images become inadequate by blockage in front of camera, these unwanted blocking materials could be removed with the help of inpainting method, this is explained with the help of images with unknown ground truth data such as Lincoln Image, Pool Table, Tower image etc. The different parameters used for the purpose of inpainting are, fractional order, $r = 0.1$, confidence term regularisation, $\omega = 0.7$, component weights of confidence and data term, $\alpha = 0.5,\ \beta = 0.5$. The results of the presented method are demonstrated in the following figures.

4.1 Synthetic Images

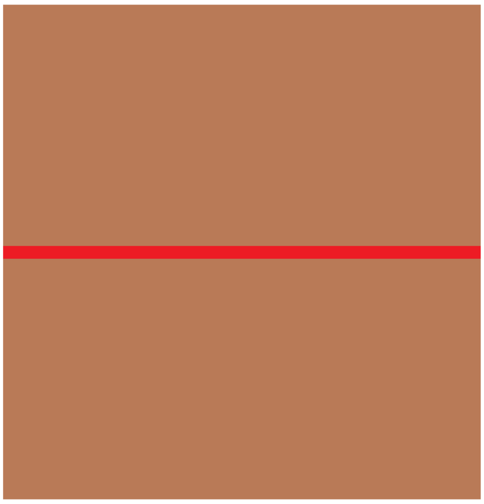
Following are the synthetic images of different sizes with irregularities in them, which causes them to look absurd, are used for the testing the reconstructing capability and performance of the defined algorithm.



(a)



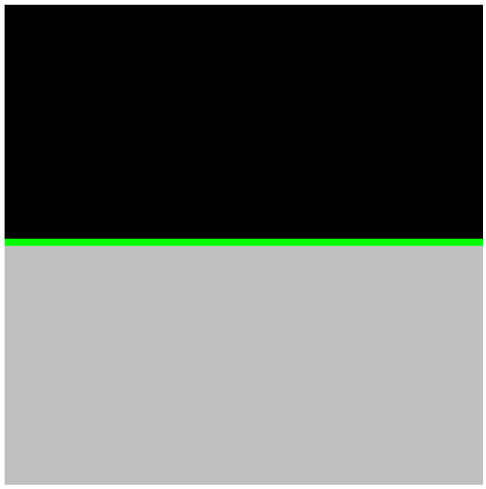
(b)



(c)

Figure 4.1 (a) Test image 1 (156×150) with a break in centre, (b) Test image 1 (156×150) with break area masked with green colour, (c) Inpainted test image 1 (156×150) which resembles the original image.

(a)



(b)

(c)

Figure 4.2 (a) Test image 2 (284×213) with the irregularity in centre line [42], (b) Test image 2 (284×213) with irregularity masked with green colour, (c) Inpainted test image 2 (284×213) which resembles the original Image.

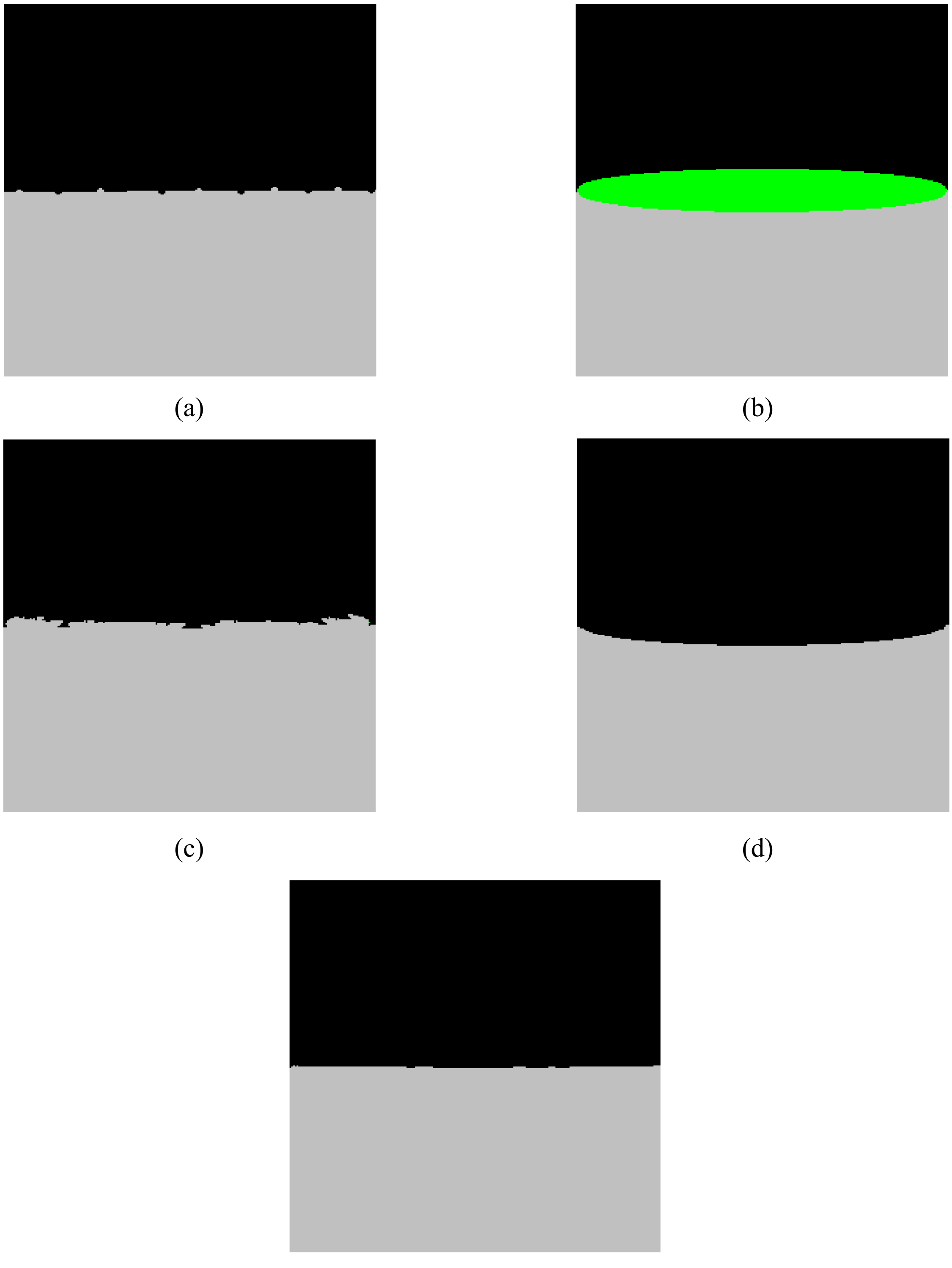
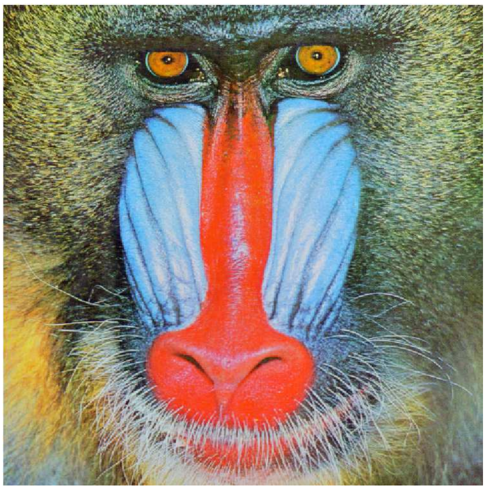


Figure 4.3 (a) Test image 3 (284×213) with the irregularity in centre line [42], (b) Test image 3 (284×213) with irregularity masked with green colour, (c) Inpainted test image 3 (284×213) with Criminisi [6] method, (d) Inpainted test image 3 (284×213) with Chandersekran [3] method, (e) Inpainted test image 3 (284×213) with proposed method.

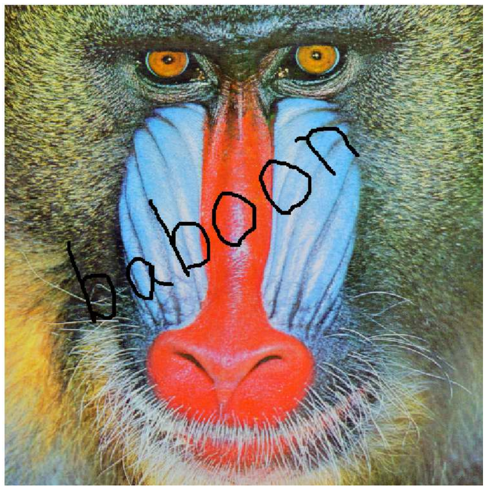
In these synthetic images of different sizes, irregularities present are removed with the defined method and comparison is done with existing methods as shown in Figure 4.3. In Criminisi method, the resultant image have some zigzag lines and Chandersekran method have done inpainting along the curved line whereas the proposed method results in nearly straight line as required. The proposed scheme is further confirmed by the performing the algorithm on images with known and unknown ground truth data.

4.2 Images with Known Ground Truth Data

Following are the images of different sizes with known ground truth data, that is, original image for the calculation purpose of performance metrics MSE, PSNR and SSIM.



(a)



(b)

(c)

Figure 4.4 (a) Baboon image (512×512) [42], (b) Baboon image (512×512) with text written on it, (c) Resultant Baboon image (512×512) obtained after removing text and inpainting the region thereafter.

(a)

(b)

(c)

Figure 4.5 (a) Bungee jumper image (308 × 206) [3], (b) Bungee jumper image (308 × 206) with text written on it, (c) Resultant Bungee jumper image (308 × 206) obtained after removing text and inpainting the region thereafter.

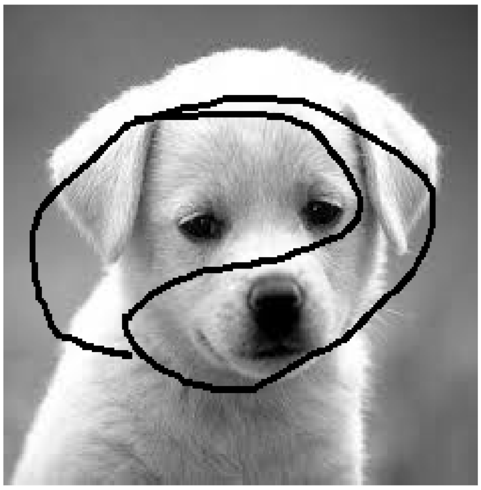
(a)

(b)

(c)

Figure 4.6 (a) Cat image (133×490) [42], (b) Cat image (133×490) with text written on it, (c) Resultant Cat image (133×490) obtained after removing text and inpainting the region thereafter.

(a)



(b)

(c)

Figure 4.7 (a) Dog image (213×236) [42], (b) Dog image (213×236) with scratch on it, (c) Resultant Dog image (213×236) obtained after removing scratch and inpainting the region thereafter.

(a)

(b)

(c)

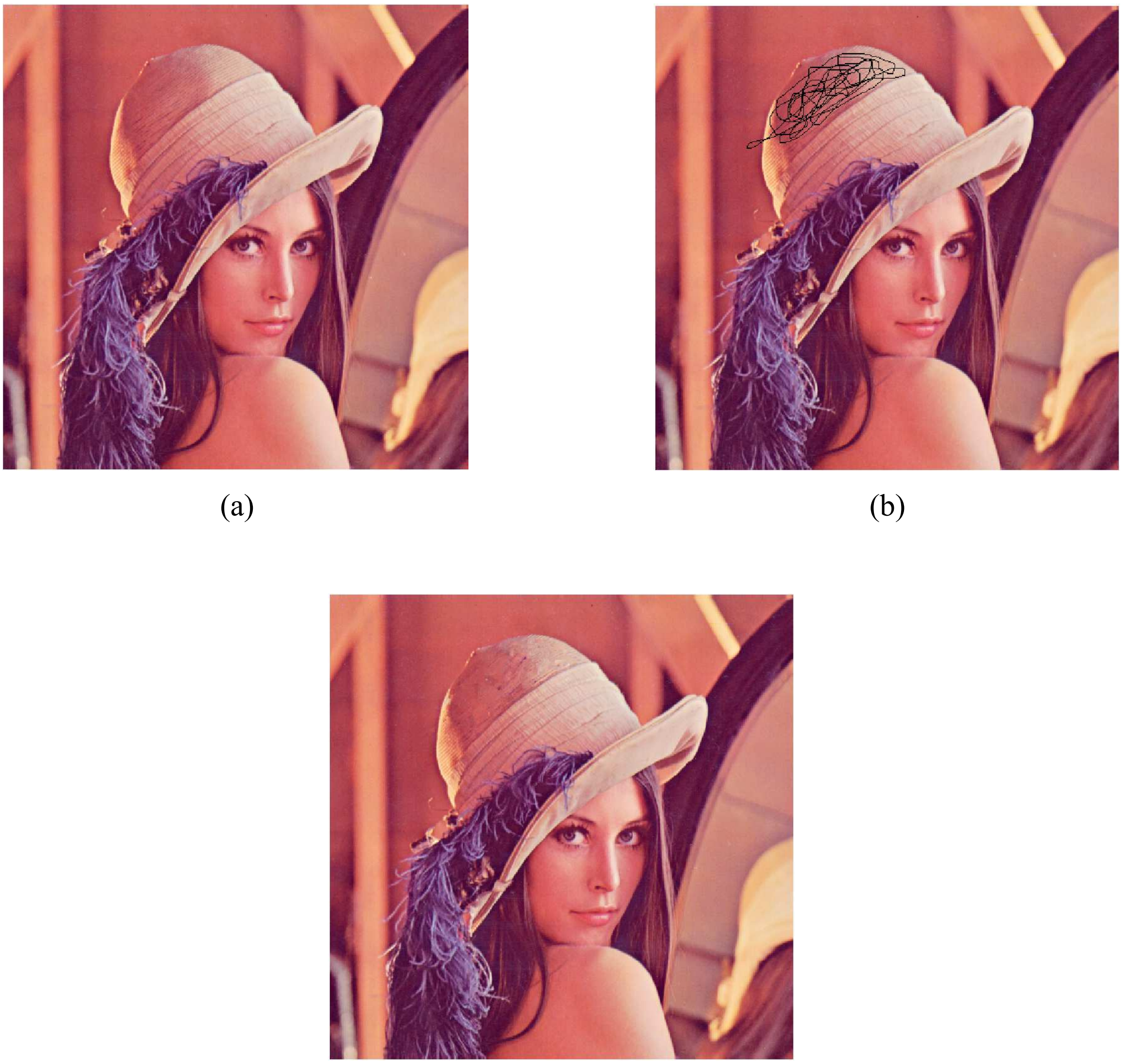
Figure 4.8 (a) Fruits image (512×512) [42], (b) Fruits image (512×512) with text written on it, (c) Resultant Fruits image (512×512) obtained after removing text and inpainting the region thereafter.

(a)

(b)

(c)

Figure 4.9 (a) Jeep image (254×381) [3], (b) Jeep image (254×381) with text written on it, (c) Resultant Jeep image (254×381) obtained after removing text and inpainting the region thereafter.



(a) (b)

(c)

Figure 4.10 (a) Lena image(512×512) [42], (b) Lena image (512×512) with scratches on hat in it, (c) Resultant Lena image (512×512) obtained after removing the scratch and inpainting the region thereafter.

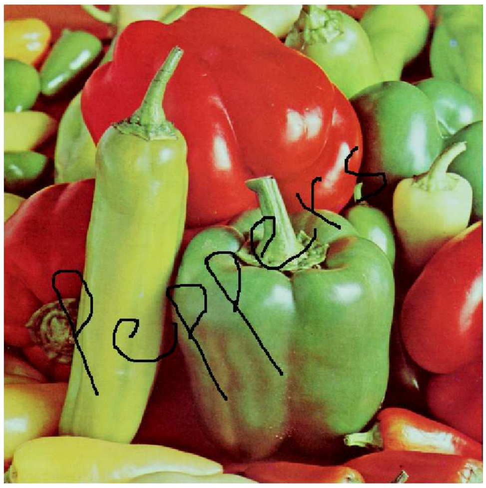
(a)

(b)

(c)

Figure 4.11 (a) Mountain image (481×321) [43], (b) Mountain image (481×321) with text written on it, (c) Resultant Mountain image (481×321) obtained after removing the text and inpainting the region thereafter.

(a)



(b)

(c)

Figure 4.12 (a) Pepper image (512 × 512) [42], (b) Pepper image (512 × 512) with text written on it, (c) shows the Resultant Pepper image (512 × 512) obtained after removing the text and inpainting the region thereafter.

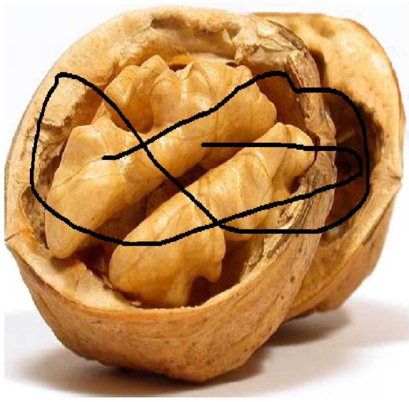
(a)

(b)

(c)

Figure 4.13 (a) Tomb image (481×321) [43], (b) Tomb image (481×321) with text written on it, (c) Resultant Tomb image (481×321) obtained after removing the text and inpainting the region thereafter [43].

(a)



(b)

(c)

Figure 4.14 (a) Walnut image (332×470) [43], (b) Walnut image (332×470) with scratch on it, (c) Resultant Walnut image (332×470) obtained after removing the scratch and inpainting the region thereafter.

The algorithm described above successfully removes text and scratch intentionally added to various images with varying sizes as shown in the above figures. This algorithm can be applied to images with date stamped on them and removing the watermarks. The performance metrics depicting the efficiency of the presented algorithm is compared in terms of parameters MSE, PSNR, SSIM for the above images are illustrated in the Tables 4.1, Table 4.2, Table 4.3.

4.3 Images with Unknown Ground Truth Data

Following are the images of different sizes with unknown ground truth data, that is, original image will be changed after applying the algorithm.

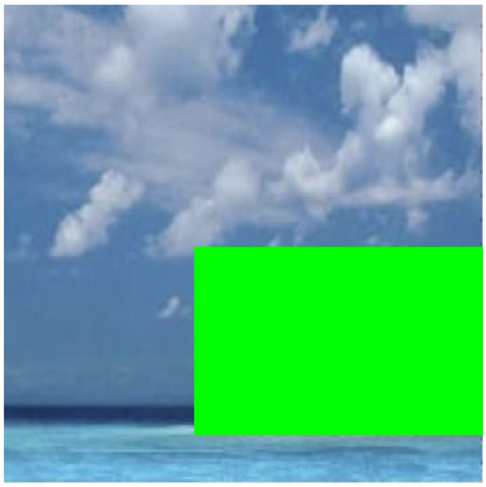
(a)

(b)

(c)

Figure 4.15 (a) Bungee jumper image (308×206) [3], (b) Bungee jumper image (308×206) with bungee jumper masked with green colour for removal process, (c) Resultant Bungee jumper image (308×206) obtained after removing jumper and inpainting the region thereafter.

(a)

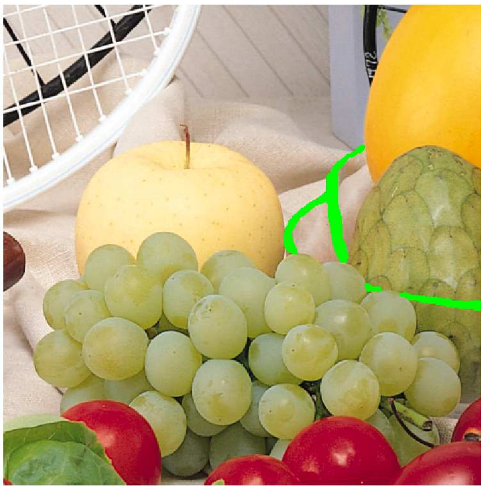


(b)

(c)

Figure 4.16 (a) Island image (279×365) [3], (b) Island image (279×365) with island masked with green colour for removal process, (c) Resultant Island image (279×365) obtained after removing island and inpainting the region thereafter.


(a)


(b)


(c)

Figure 4.17 (a) Fruits image (512×512) [42], (b) Fruits image (512×512) with silver rod masked with green colour for removal process, (c) Resultant Fruits image (512×512) obtained after removing silver rod and inpainting the region thereafter.

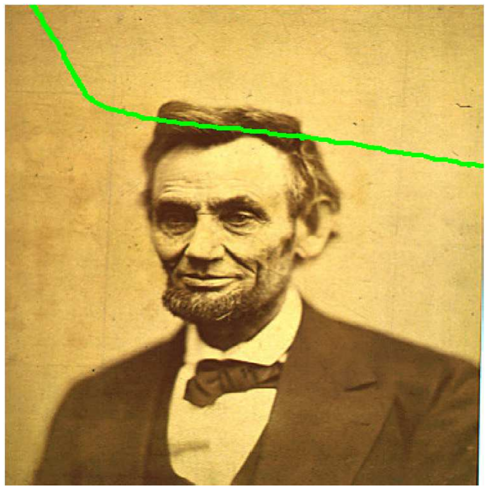
(a)

(b)

(c)

Figure 4.18 (a) Jeep image (254×381) [3], (b) Jeep image (254×381) with person tied with rope masked with green colour for removal process, (c) Resultant Jeep image (254×381) obtained after removing person tied with rope and inpainting the region thereafter.

(a)



(b)

(c)

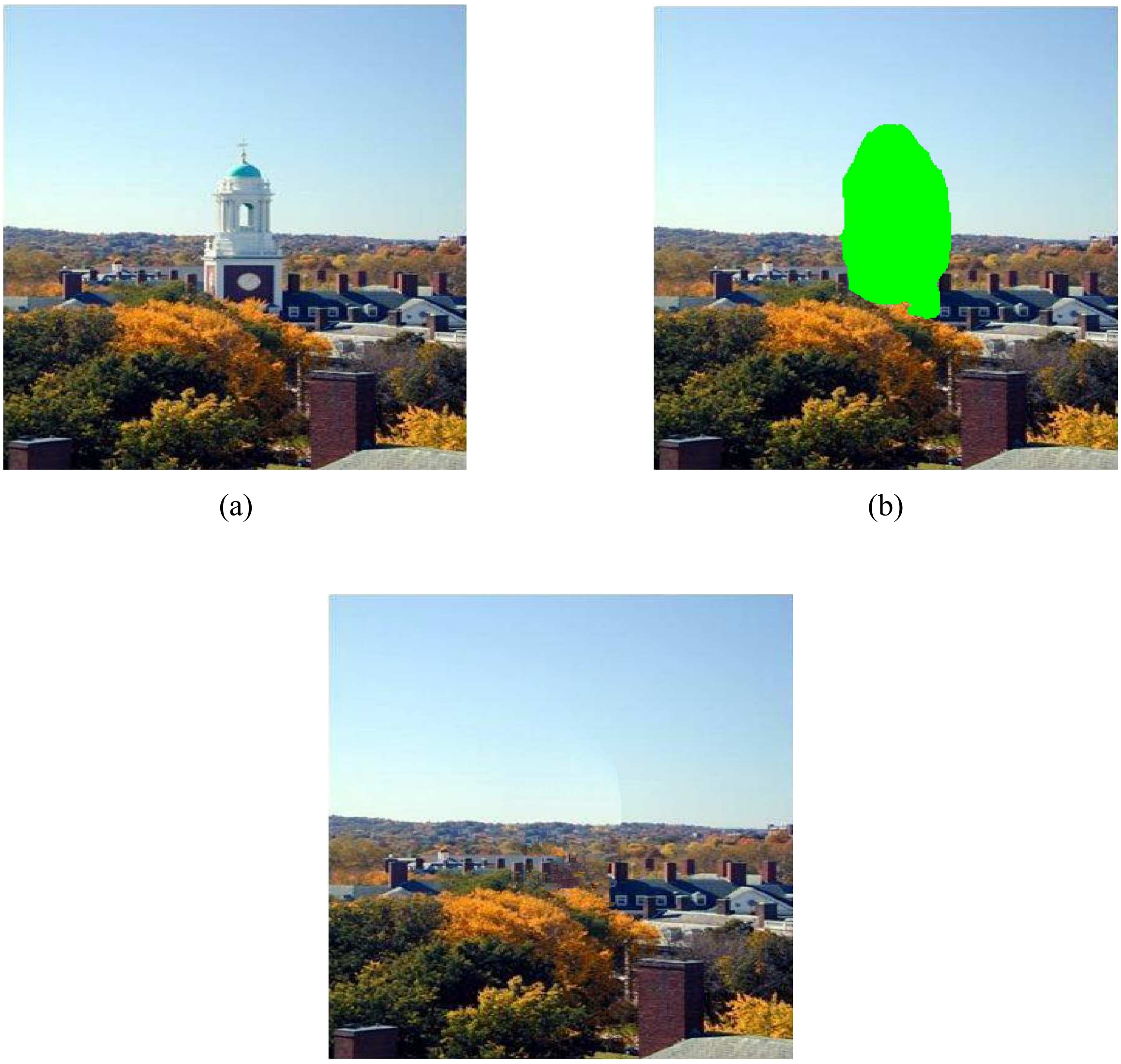
Figure 4.19 (a) Lincoln image (432 × 371) [43], (b) Lincoln image (432 × 371) with a scratch on top masked with green colour for removal process, (c) Resultant Lincoln image (432 × 371) obtained after removing scratch and inpainting the region thereafter.

(a)

(b)

(c)

Figure 4.20 (a) Pool Table image (383 × 510) [42], (b) Pool Table image (383 × 510) with a cube on bottom masked with green colour for removal process, (c) Resultant Pool table image (383 × 510) obtained after removing cube and inpainting the region thereafter.



(a) (b)

(c)

Figure 4.21 (a) Tower image (402×302) [43], (b) Tower image (402×302) with a tower masked with green colour for removal process, (c) Resultant Tower image of size (402×302) obtained after removing tower and inpainting the region thereafter.

Above figures shows the successful removal of the desired object as marked with the green colour. Results look pleasing and appear not to be tempered and are authentic in nature. Image obtained from satellite and red eye caused due to impaired working of camera with photographic flash in low ambience light could be removed with inpainting technique. It is no possible to calculate the MSE, PSNR, SSIM as image characteristics change after the removal process.

4.4 Comparative Analysis

The comparison of Criminisi method, Chandersekran and the proposed algorithm is done in the form of performance metrics such as MSE, PSNR, SSIM for the various images with known ground truth having different sizes.

Table 4.1: MSE Comparison for Different Methods

Image	Criminisi Method [6] MSE	Chandersekran Method [3] MSE	Proposed Method MSE	Improvement from Criminisi Method [6] MSE	Improvement from Chandersekran Method [3] MSE
Baboon	10.2280	8.9952	7.9896	1.2684	1.0056
Bungee	45.4703	40.3521	38.3447	7.1256	2.0074
Cat	2.7210	2.1821	2.0390	0.682	0.1431
Dog	15.6712	8.4750	7.4235	8.4277	1.0515
Fruits	3.8711	0.7453	0.6275	3.2436	0.1178
Jeep	8.5335	3.6129	2.8962	5.6373	0.4204
Lena	9.5015	5.2964	4.8760	4.6255	0.4204
Mountain	1.5051	1.3502	1.3354	0.1697	0.0148
Pepper	4.2465	3.4976	3.4542	0.7923	0.0434
Tomb	8.7826	8.8491	8.3035	0.4791	0.5456
Walnut	17.3449	12.8511	12.6672	4.6777	0.1839

The Table 4.1 shows the reduction achieved in MSE by presented algorithm ranging from minimum value of 0.16 in Mountain image, 4.6253 in Lena image and maximum value of 8.4277 in Dog image depending upon the size of images used from Criminisi Method and in Chandersekran Method, minimum reduction of 0.0148 in Mountain image, 1.0515 in Dog image and maximum of 2.0074 in case of Bungee jumper image.

Table 4.2: PSNR (dB) Comparison for Different Methods

Image	Criminisi method [6] PSNR (dB)	Chandersekran Method [3] PSNR (dB)	Proposed Method PSNR (dB)	Improvement from Criminisi Method [6] PSNR (dB)	Improvement from Chandersekran Method [3] PSNR (dB)
Baboon	38.0329	38.5907	38.6939	0.5750	0.1125
Bungee	31.5535	32.0721	32.2937	0.7402	0.2216
Cat	43.7835	44.7420	45.0366	1.2531	0.2946
Dog	36.1798	38.8494	39.4247	3.2449	0.5753
Fruits	42.2524	49.4077	50.1548	7.9024	0.7471
Jeep	38.8195	42.5522	43.5125	4.6931	0.9603
Lena	38.3529	40.8910	41.2501	2.8972	0.3591
Mountain	46.3552	46.8267	46.9248	0.1596	0.1625
Pepper	41.8505	42.6932	42.8749	1.0244	0.1817
Tomb	38.6946	38.6618	38.9382	0.2436	0.2764
Walnut	35.7391	37.0414	37.1440	1.3649	0.1261

The Table 4.2 shows the improvement achieved in PSNR by presented algorithm ranging from minimum value of 0.1596 dB in Mountain image, 2.8972 dB in Lena image and maximum value of 7.9024 dB in Fruits image depending upon the size of images used from Criminisi Method and in Chandersekran Method, minimum reduction of 0.1125 dB in Baboon image, 0.5753 dB in Dog image and maximum of 0.9603 dB in case of Jeep image.

Table 4.3: SSIM Comparison for Different Methods

Image	Criminisi method [6] SSIM	Chandersekran Method [3] SSIM	Proposed Method SSIM	Improvement from Criminisi Method [6] SSIM	Improvement from Chandersekran Method [3] SSIM
Baboon	0.9963	0.9963	0.9964	0.0001	0.0001
Bungee	0.9825	0.9845	0.9846	0.0021	0.0001
Cat	0.9989	0.9991	0.9992	0.0003	0.0001
Dog	0.9767	0.9835	0.9838	0.0071	0.0003
Fruits	0.9982	0.9991	0.9992	0.0010	0.0001
Jeep	0.9936	0.9959	0.9960	0.0024	0.0001
Lena	0.9977	0.9986	0.9987	0.0010	0.0001
Mountain	0.9981	0.9982	0.9983	0.0002	0.0001
Pepper	0.9985	0.9987	0.9989	0.0004	0.0002
Tomb	0.9967	0.9970	0.9971	0.0004	0.0001
Walnut	0.9973	0.9978	0.9979	0.0006	0.0001

The Table 4.3 shows the improvement achieved in SSIM by presented algorithm ranging from minimum value of 0.0001 in Baboon image, 0.0010 in Lena image and maximum value of 0.0071 in Dog image depending upon the size of images used from Criminisi Method and in Chandersekran Method, minimum reduction of 0.0001 in most of images, 0.0002 in Peppers image and maximum of 0.0003 in case of Dog image.

4.5 Summary

The algorithm is implemented on various synthetic images, images with ground truth data and with unknown ground truth data of different sizes. The proposed algorithm provides better results for the synthetic images as compared to the existing algorithms. The texts written or scratches made manually in case of images with known ground truth data are successfully removed resulting in the images which looks like original image. Then, it is applied on images with unknown ground truth data for effectively removing the undesired object. Results in case of images with known ground truth data show improvement in terms of MSE, PSNR and SSIM as compared to the previous work as depicted. In case of removing the objects from images, it’s characteristics change, so comparison can’t be done, because there is no original image for comparison purpose, that is why these are called images with unknown ground truth data.

Chapter-5

Conclusion and Future scope

5.1 Conclusion

In this dissertation, firstly introduction about inpainting process and guidelines which must be kept in mind while deciding a technique are given. Then various techniques for texture synthesis, structure propagation and image inpainting are discussed in the literature. The importance of confidence and data terms are illustrated. Exemplar-based inpainting uses the based filling order prioritization based on the fractional gradient function for the calculation of data term which proves to be more efficient in differentiating edges. A new improved confidence term is used as previous one decreases exponentially, hence reducing to zero value if the algorithm takes higher number of iterations causing the incorrect patch filling order and resulting in faulty completed image. Algorithm is proposed by incorporating improved confidence term discussed, in above said fractional method. The proposed algorithm is tested on different test images and real world images by removing written text and removing a desired/unwanted object from the image so that resultant image looks authentic and results are found to be better and more efficient than the present traditional techniques in terms of performance metrics MSE, PSNR and SSIM. From Criminisi Algorithm, there is an increase of PSNR ranging from 0.24 dB to 7.90 dB and from Chandersekran method, increase of 0.1 dB to 0.96 dB is achieved. Also the final image looks more legitimate to the human eye as it should not appear to be tempered with.

5.2 Future Scope

- Instead of searching for a patch within the same image, a more generic approach could be extended for the source region to a database of images. In this case, best exemplar patch will be searched over all images in database.
- Patch size used could be made image specific through machine learning algorithms.

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