

4. Chapter 4

## **CHAPTER 4**

# **MODIFIED EXEMPLAR APPROACH FOR INPAINTING**

## 4. MODIFIED EXEMPLAR APPROACH FOR INPAINTING

### 4.1 Introduction

Image inpainting is a method in which missed data are recovered and used in reconstructing the missing region. Exemplar-based inpainting which is also known as texture-oriented inpainting where samples of required texture are used for synthesis. One of the important works in Exemplar-based image inpainting is carried out by (Criminisi et al. 2004). In this section, we provide a detailed explanation of Criminisi approach of image inpainting. This algorithm combines the advantage of texture synthesis method and PDE-based inpainting method. The method proposed in this work consists of the following major steps for filling the missing region.

- i. The input to the algorithm is an image with a missing region.
- ii. The pixels on the edge of the missing region, fill front are considered.
- iii. The strength of a pixel on the fill front is calculated to prioritise the pixel to form a patch.
- iv. Find the most similar patch from the known region.
- v. The prioritised patch is matched against a patch of the same size from the known region.
- vi. Once the most similar patch is obtained, the prioritised pixel and the patch surrounding are replaced.

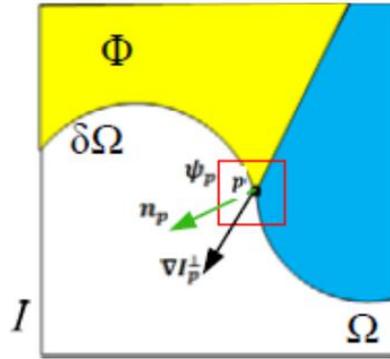


Figure 4.1: Image Representing Partial Loss of Data

Figure 4.1 gives an introduction to the terms used in the algorithm.

- i.  $I$  represent the whole image that includes both the known region and the occluded region that is to be filled.
- ii. Let  $\Omega$  represent the target region where the pixels are missing and this is the region that needs to be recovered.
- iii.  $\Phi$  represents the source region from which a most similar patch is selected to fill the target region.
- iv.  $\delta\Omega$  represent the contour of the region to be filled. This is also being known as fill front.
- v.  $\Psi_p$  is the patch surrounding the pixel  $p$ .

The pixels are prioritised from the fill front and appropriate patch is chosen around the prioritised pixel. Once the patch is found, pixels are diffused inwards. To prioritise the pixels on the fill front, the confidence term of the pixel and the data term of the pixel are used. Figure 4.2 clearly explains the procedure followed in filling pixels using the above method.

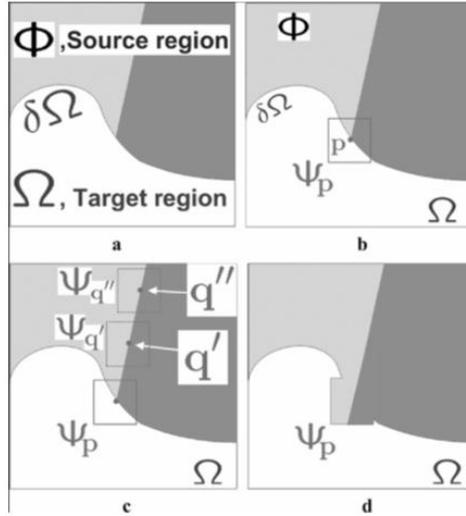


Figure 4.2: Procedure of Inpainting.

The square template  $\Psi_p$  is the patch centred at  $p$ . the pixel  $p$  belongs to  $\delta\Omega$ . The patch  $\Psi_p$  has at its centre, the pixel  $p$ . If  $\Psi_p$  lies in the continuation of an edge, the most similar match  $\Psi_q \in \Phi$  also lies in the same edge.

## 4.2 Procedure of Inpainting

From the given input image in Figure 4.2(a), the target region  $\Omega$  is selected. The source region  $\Phi$  is the whole image that is  $I$  minus the target region,  $\Omega$ .

$$\Phi = I - \Omega \quad (4.1)$$

The patch  $\Psi$  is to be specified with a size. In this method the size is considered as the default size  $9 \times 9$  pixels. According to the algorithm, each pixel maintains a colour value and a confidence value. The colour value will be empty if the pixel is not filled. The confidence value is fixed once the pixel is filled. The pixels along the fill front (contour) are given

temporary priority value to determine the order of filling. The algorithm consists of three basic steps on which iteration follows.

i. Computation of patch priority

The priority is given to each pixel on the fill front based on if the pixel is a continuation of the strong edge and if they are surrounded by high confidence pixels.

For a patch  $\Psi_p$  with center at  $p$  for any  $p \in \delta\Omega$ , the priority  $P(p)$  of that pixel is set to the equation,

$$P(p) = C(p)D(p) \quad (4.2)$$

Where  $C(p)$  is the confidence term and  $D(p)$  is defined as the data term and given as,

$$C(p) = \frac{\sum_{q \in \Psi_p \cap \emptyset} C(q)}{|\Psi_p|}, 0 \leq C \leq 1 \quad (4.3)$$

$$D(p) = \frac{\nabla I_p \cdot n_p}{\alpha} \quad (4.4)$$

In equation 4.3,

- i.  $C(p)$  defines the confidence term of the pixel  $p$ .
- ii.  $\Psi_p$  represents the patch with pixel  $p$  at the centre.
- iii.  $\emptyset$  is the source region which is defined as  $I - \Omega$ .

In equation 4.4,

- i.  $D(p)$  is known as the data term.
- ii.  $|\Psi_p|$  designates the area of the patch  $\Psi_p$

- iii.  $\alpha$  is the normalization factor. Since the image is represented as a grey scale image,  $\alpha$  is considered as 255.
- iv.  $n_p$  denote a unit vector orthogonal to the front  $\delta\Omega$  in the point at pixel  $p$ .
- v.  $\nabla I'_p$  Signifies the orthogonal operator.

With the above equation, the priority value  $P(p)$  for each pixel on the contour is calculated. The value of  $C(p)$  is initialised at the beginning of the algorithm as in equation 4.5 and 4.6.

$$C(p) = 0 \text{ for all } p \in \Omega \quad (4.5)$$

$$C(p) = 1 \text{ for all } p \in I - \Omega \quad (4.6)$$

$C(p)$  is the confidence term that gives information of the surrounding pixels around  $p$ . Those patches that have more of the pixels around it available are the patches that are prioritized for filling. The data term  $D(p)$  defines the strength of the isophote that is selected at  $\delta\Omega$  at each of the iteration in the filling process. Hence, this will enhance the priority of a patch. This will help the linear structure to be synthesized first in the filling process.

## ii. Structure Information

Once the priorities of the pixels in the fill front are computed, the patch with the highest priority is found as  $\Psi_{p'}$ . This patch is filled with the patch that is matched from the source region  $\emptyset$ . The most similar patch is searched in the source as

$$\Psi_{q'} = \arg \min_{\Psi_q \in \emptyset} d(\Psi_{p'}, \Psi_q) \quad (4.7)$$

Here the distance between  $\Psi_p$  and  $\Psi_{p'}$  are calculated using the sum of square differences (SSD).

Once the source patch is found, the value of the pixel that is to be filled in the target region say  $p'$  where

$$p' \in \Psi_{p \cap \Omega} \quad (4.8)$$

is taken from its corresponding position of the source patch  $\Psi_p$ .

$$C(p) = C(p') \forall p \in \Psi_{p'} \cap \Omega \quad (4.9)$$

### **4.3 Modified Exemplar method**

In this work, the Criminisi algorithm is modified in finding the priority of the best pixel on the contour and further finding the proper match among the known pixels.

Table 4.1: Modified Exemplar algorithm.

<p><b>I: The whole image</b></p> <p><b><math>\Omega</math>: The portion of the image I that is occluded</b></p> <p><b><math>\Psi_p</math>: the patch formed for a search</b></p> <p>Step 1: <i>If</i> <math>p \in I</math></p> <p style="padding-left: 40px;"><math>C(p)=0</math>;</p> <p><i>else</i></p> <p style="padding-left: 40px;"><math>C(p)=1</math>;</p> <p>Step 2: <i>For</i> all pixels on the fill front</p> <p>{</p> $C(p) = \frac{\sum_{q \in \Psi_p \cap \Omega} C(q)}{ \Psi_p }, 0 \leq C \leq 1$ <p style="padding-left: 40px;">Calculate gradient magnitude <math>D(p) = \sqrt{G_x^2 + G_y^2}</math></p> <p style="padding-left: 40px;">Calculate <math>C(p).D(p)</math></p> <p>}</p> <p><i>Continue</i></p> <p>Step 3: Form a patch <math>\Psi_p</math> with p as the pixel at center.</p> <p>Step 4: <i>For</i> all <math>p \in I - \Omega</math></p> <p style="padding-left: 40px;">Find the most similar patch <math>\Psi_p'</math></p> <p>Step 5: Replace the similar patch with <math>\Psi_p</math></p> <p>Step 6: Repeat step2 to step 6 until <math>\Omega</math> is filled.</p>
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The above algorithm is explained in detail below.

Step 1: The target region initialization. In this step, the missing areas in the image are identified.

Step 2: Computation of patch priority.

The priority is given to each pixel on the fill front based on if the pixel is a continuation of the strong edge and if they are surrounded by high confidence pixels.

For a patch  $\Psi_p$  with center at  $p$  for any  $p \in \delta\Omega$ , the priority  $P(p)$  of that pixel is set with the equation,

$$P(p) = C(p)D(p) \quad (4.10)$$

Where  $C(p)$  is the confidence term and  $D(p)$  is defined as the data term.

During initialisation the values of  $C(p)$  is set as:

$$C(p) = 0 \text{ for all } p \in \Omega$$

(4.11)

$$C(p) = 1 \text{ for all } p \in I-\Omega \quad (4.12)$$

$C(p)$  is a confidence term that gives information of the surrounding pixels around  $p$ . Those patches that have more of the pixels around it available are the patches that are prioritized for filling.

$$C(p) \text{ is calculated as } C(p) = \frac{\sum_{q \in \Psi_p \cap \Omega} C(q)}{|\Psi_p|}, 0 \leq C \leq 1$$

(4.13)

To calculate the data term, sobel edge detector is used to find the strength of the pixel on the edge. As larger mask reduce the error rate, in this case a mask of 2 is used with  $c=2$ , Vincent and Folorunso (2009).

This leads to a sobel operator,

$$M_x = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix} \quad \text{and} \quad M_y = \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$$

The major steps in finding the magnitude of the gradient are as given in Table below.

Table 4.2: Sobel Edge Detection.

<p>Step 1: Smooth the input image <math>\hat{f}(x, y) = f(x, y) * G(x, y)</math></p> <p>Step 2: <math>\hat{f}_x = \hat{f}(x, y) * M_x(x, y)</math></p> <p>Step 3: <math>\hat{f}_y = \hat{f}(x, y) * M_y(x, y)</math></p> <p>Step 4: <math>magn(x, y) =  \hat{f}_x  +  \hat{f}_y </math></p> <p>Step 5: <math>dir(x, y) = \tan^{-1} \left( \frac{\hat{f}_x}{\hat{f}_y} \right)</math></p> <p>Step 6: If <math>magn(x, y) &gt; T</math>, Then possible edge point.</p>
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Step 3: For every patch, the most similar patch from the source region is selected. This is done on the basis of structural similarity measure (SSIM).

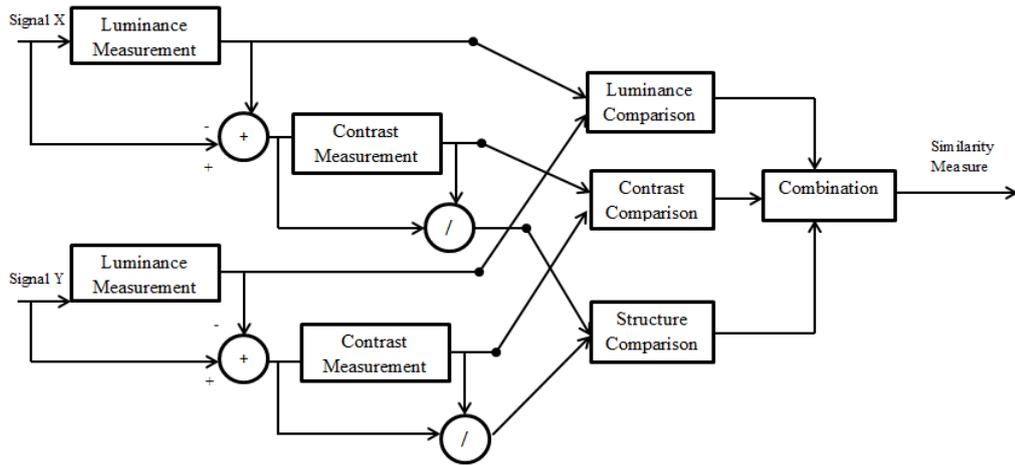


Figure 4.3: Structural Similarity Measure Architecture.

Figure 4.3 explains the system diagram of similarity measurement. Considering  $x$  and  $y$  to be the image signals, from the target patch and the patch considered for match. The similarity index can serve as the quantitative measure for the quality of the second signal. The task of similarity index is divided into three different comparisons: luminance, contrast and structure. As a first step, luminance of each of the signal is compared followed by removing the intensity from the signal and further signal is normalized by its own standard deviation. Structure comparison is been calculated on the normalized signals. Overall similarity measure is calculated combining the above three components.

Step 4: Searching for the best patch starts from the patch of pixels around the target patch saving the computational time for patch selection.

Step 5: Replace the target patch with the most similar patch identified.

The above procedure can be summarised as below in Table 4.3.

Table 4.3: Summary of the Modified Exemplar Approach

<p>I = image to be recovered</p> <p><math>\Omega</math> = the occluded or the missing region</p> <p>I-<math>\Omega</math> = the known region</p> <ul style="list-style-type: none"> <li>• To prioritise a pixel for filling compute C(p).D(p)</li> <li>• C(p) is calculated as <math>C(p) = \frac{\sum_{q \in \Psi_p \cap \Omega} C(q)}{ \Psi_p }</math>, <math>0 \leq C \leq 1</math></li> <li>• Calculate gradient magnitude <math>D(p) = \sqrt{G_x^2 + G_y^2}</math></li> <li>• The priority pixel is bound by a 9×9 pixel that makes the patch</li> <li>• The best patch the matches with the prioritised patch are found using similarity measure.</li> </ul>
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#### 4.4 Performance Analysis

To check the performance of the proposed algorithm, various images are given as the input to the system to analyse the result after inpainting is performed on them. Figure 4.4 depicts the image by name Lena on which a part of pixels at various locations are covered with green colour. This image is subjected as input to the algorithm which could recover the lost region. The recovered image is shown in Figure 4.5.

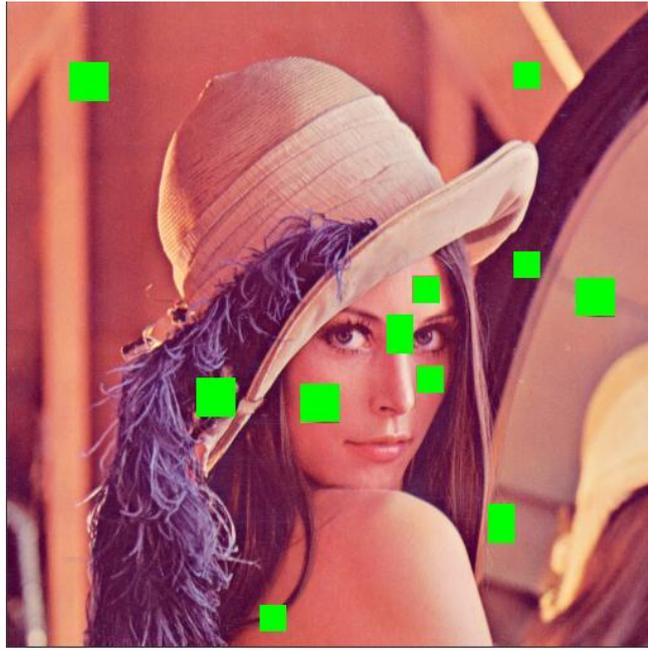


Figure 4.4: Input image1 with regions of the image covered.

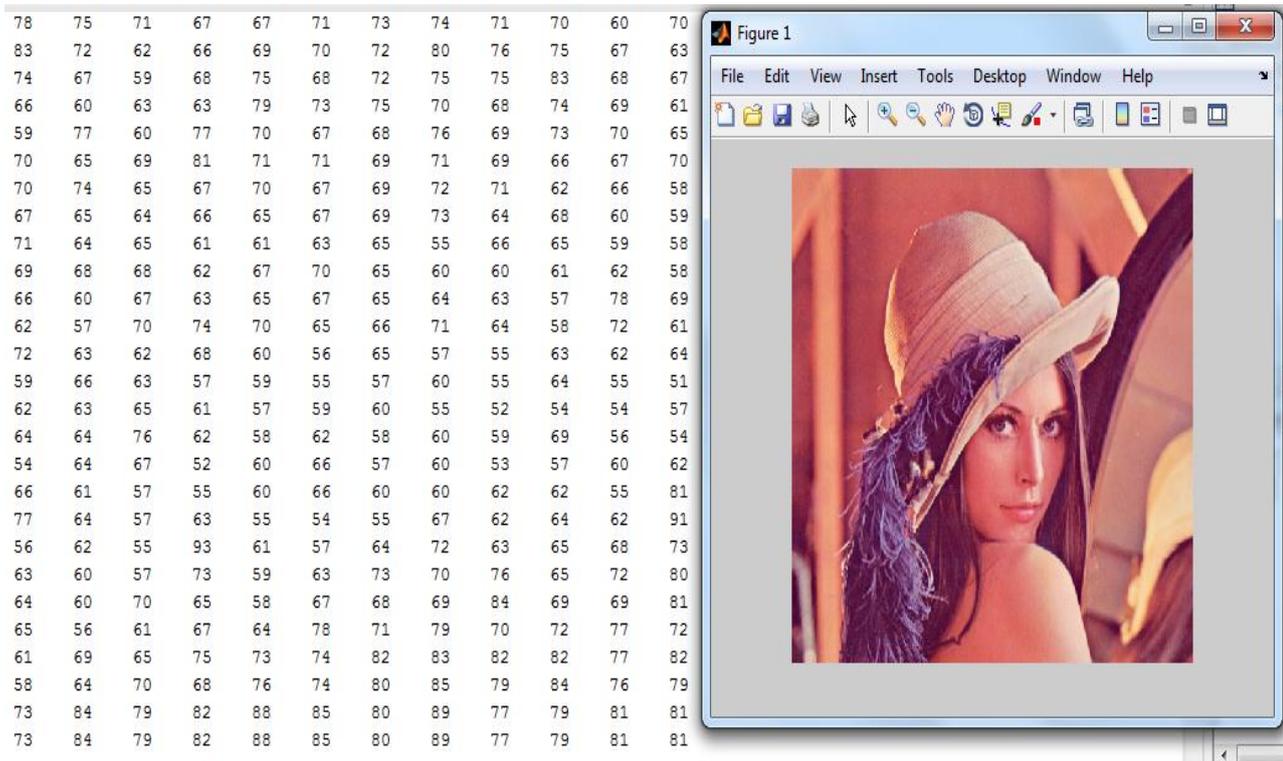


Figure 4.5: Recovering the lost region of image1.

Figure 4.6 depicts the second image as an input to the system to recover the lost region using the proposed method. The image of a building with different texture is provided as the input to identify the accuracy of recovering the lost region. The recovered image is shown in Figure 4.7.

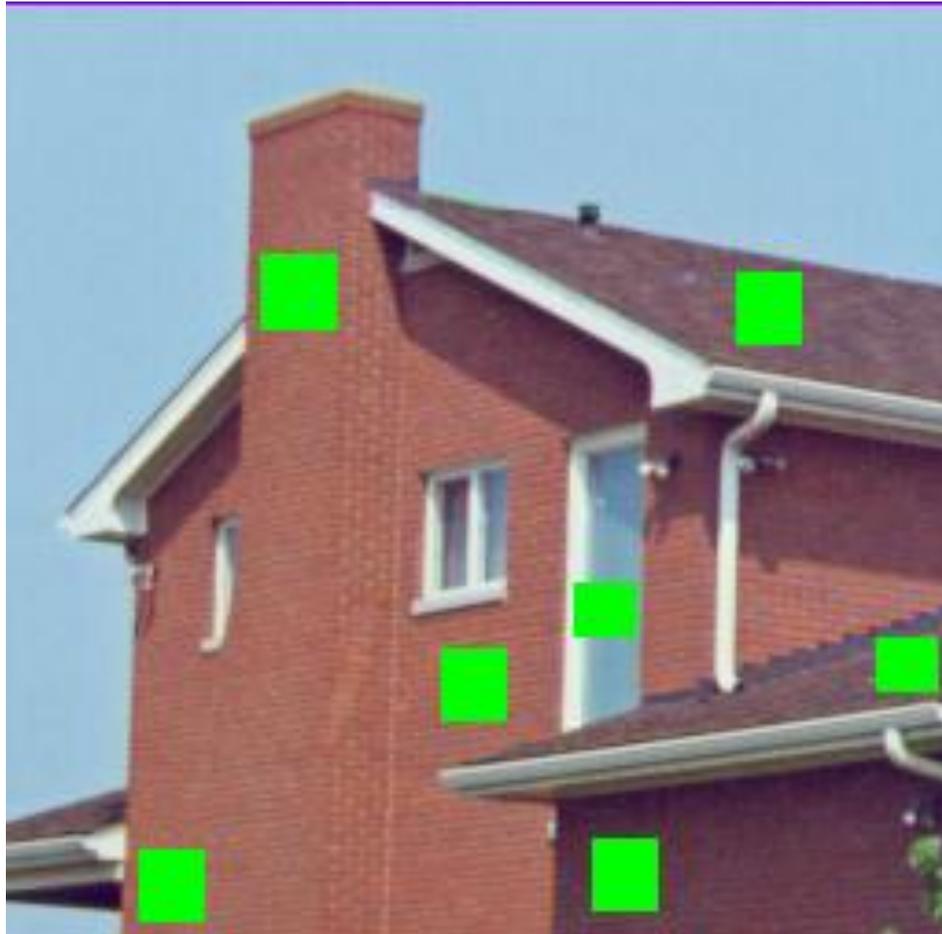


Figure 4.6: Input image2 with regions of the image covered.

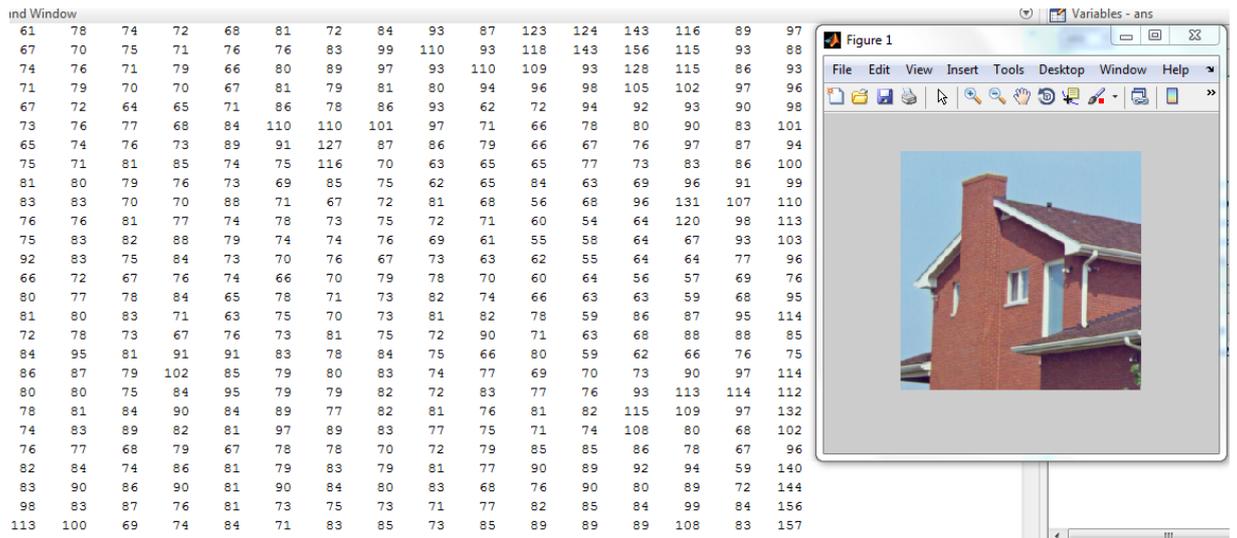


Figure 4.7: Recovering the lost region of image2

Figure 4.8 depicts the third input image called bungee that is subjected to the system to recover the lost region using the proposed method. The recovered image is shown in Figure 4.9.



Figure 4.8: Input image1 with regions of the image covered

22	23	24	24	23	21
22	21	20	20	22	25
21	22	23	23	23	24
20	21	22	23	22	25
20	21	23	26	25	22
20	22	17	18	22	23
20	21	23	25	23	21
21	22	24	24	20	20
21	23	24	23	22	20
21	23	21	21	21	22
21	23	21	21	21	22
21	23	23	22	22	21
21	22	22	22	22	21
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20	22	20	20	23	23
20	23	21	21	21	21
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20	23	23	23	23	23
20	23	22	22	22	22
20	23	21	21	21	21

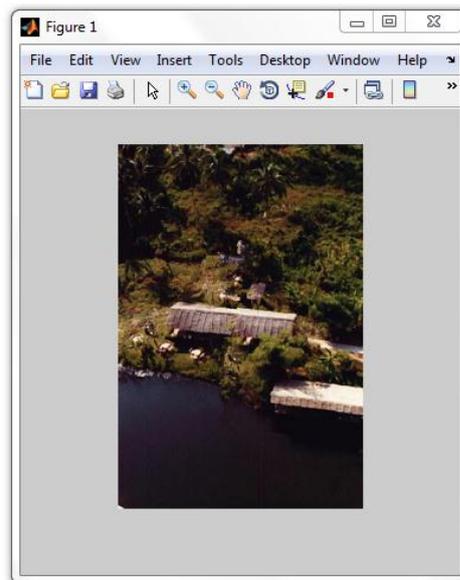


Figure 4.9: Recovering the lost region of image3

In order to check the efficiency of the proposed method, the algorithm is compared with Criminisi algorithm that uses mean square for selection of most similar patch. The input images considered are similar to those used in the study of the above two methods and filled region is replaced with white instead of green.

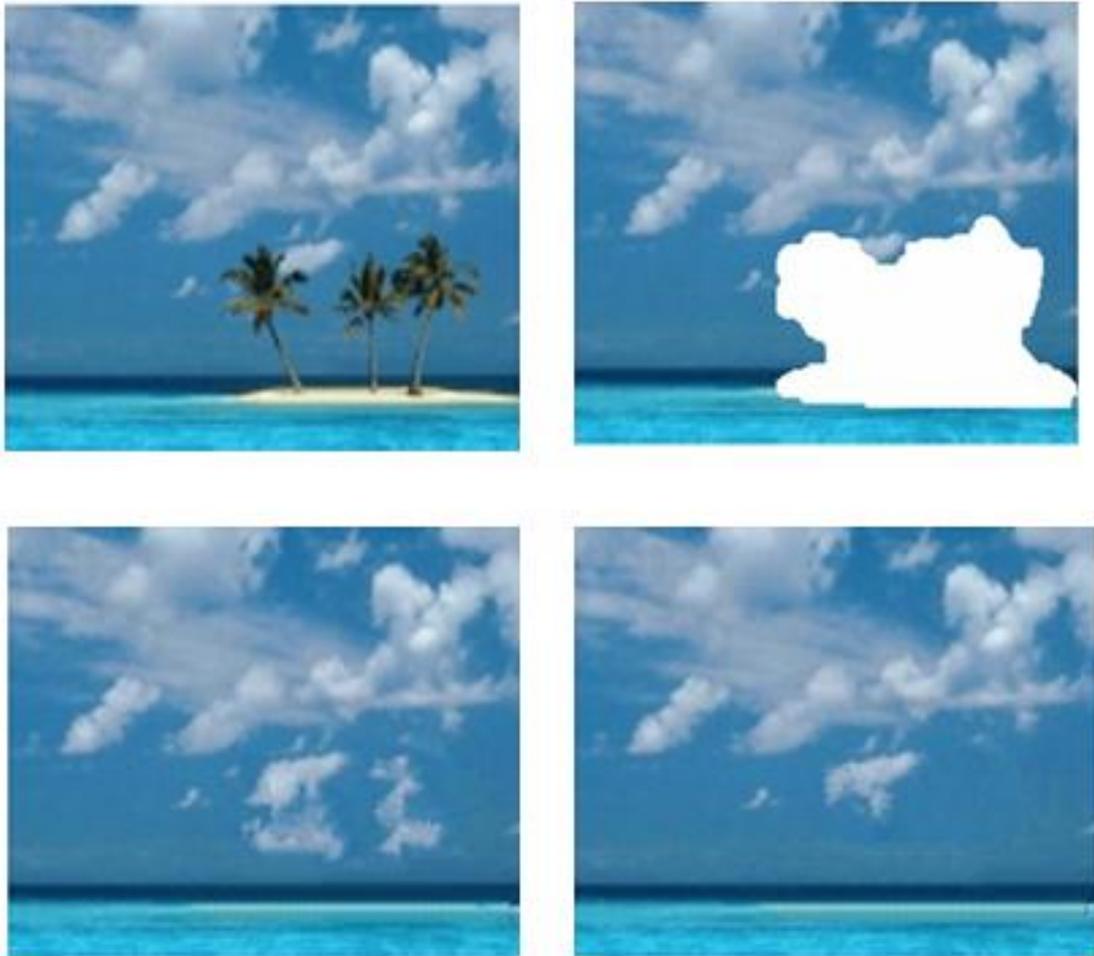


Figure 4.10: Comparative Analysis of the Modified Exemplar Inpainting.

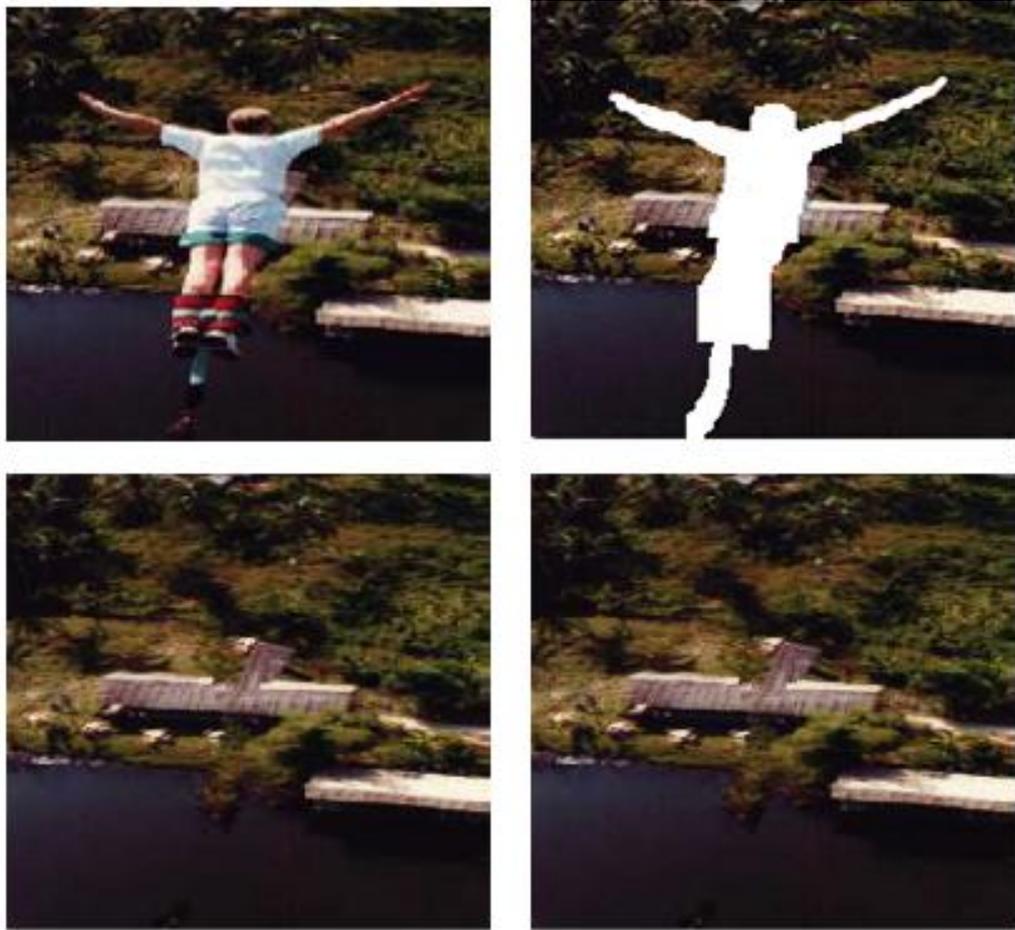


Figure 4.11: Comparative Analysis of the Modified Exemplar Approach.

From the experiment conducted that compared the proposed method with Criminisi approach, the proposed method shows a better result on recovering the lost region.

#### **4.5 Summary**

In the proposed method, an attempt is made to fill in the missing region of an image using exemplar-based image inpainting. This method of inpainting diffuses the value of the pixel from the known region. According to exemplar inpainting, a pixel from the contour of the missing region is chosen based on the priority calculating the confidence term of the pixel and strength of the pixel. To know the strength of the pixel, the magnitude of the gradient is considered. With this experiment, it is found

that Sobel gives a better understanding of the strength of a pixel on the edge. Further to find the most similar match, structural similarity measure is used. The experimental results show a better recovering of the lost pixels of an image.