# Exemplar based Image Inpainting using Advanced Wavelet Transformation

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Abstract-Image inpainting problem is one of the most essential image restoration problems. It is the technique of modifying an image in an undetectable form to an observer not familiar with the original image and is as ancient as art itself. It also refers to the practice of the artists of restoring paintings. Researchers working on different applications have adopted different names: image interpolation, disocclusion, image replacement, and error concealment though each of them carries its own individual characteristics. Earlier techniques have a very large number of problems which include lower PSNR values, high MSE values, large Time and fixed region of image to inpaint etc. This paper focus on to remove to all these problems. In this paper pattern extraction technique is used to find the best matching patch and image is inpainted on the basis of patch priority. Earlier systems for image inpainting works only on basis of neighbouring pixels but the proposed system works on the basis of patch priority of the neighbouring pixels. Proposed system follow the pattern on the basis of which it fills the targeted region of the image. In this paper Exemplar based approach along with DWT is used to inpaint the targeted pixels.

Keywords— Image inpainting, DWT, Exemplar based approach, Image Processing, Image Restoration.

#### I. Introduction

Image inpainting is the process of reconstructing the defected and lost parts of image. It is the procedure of altering a picture in an imperceptible structure to an onlooker not acquainted with the first picture and is as antiquated as workmanship itself [1]. It likewise alludes to the act of the specialists of reestablishing artistic creations. Specialists taking a shot at various applications have received diverse names: picture introduction, disocclusion, picture substitution, and mistake camouflage however each of them conveys its own individual qualities [8].

Picture rebuilding issues, for example, inpainting and deblurring have dependably been vital picture preparing errands with numerous genuine applications. One of the earliest works on digital inpainting is the work by Bertalmio et.al in where the creator's inspiration originates from the expert craftsmen who reestablish harmed antiquated compositions by hand. Often pictures may have locales with missing information. Cases may incorporate scratches on casings, scratches on pictures, the impediment of items in a

picture, or even from anomalies in the imaging gadget itself (scratched focal points) [7] [11].

To cure these issues, picture inpainting which is the lying in missing data based on known information is considered. Any similarity of request in a perception is an appearance of excess of its present representation. Such redundancies have been abused for various purposes in endless applications, one sanctioned case being information pressure. In particular, in video pressure, movement remuneration and change coding are utilized to misuse the spatio-transient repetition in the video signal. In any case, the sorts of redundancies misused by current techniques are fairly constrained. This is exemplified by the achievement of blunder camouflage procedures. In addition, Discrete cosine change (DCT), the most usually utilized change coding strategy as a part of video pressure, has been observed to be successful just for little piece sizes, which demonstrates its powerlessness to endeavor redundancies developing upto bigger degree. Wavelet has been moderately more effective in this appreciation for specific classes of pictures but hasn't found much use in general purpose video compression.

It is interesting to compare aforementioned techniques with texture synthesis and image inpainting both of which also assume the existence of redundancies in images and video, but exploit it for other purposes different from compression.

The inspiration driving present work was the perceptual nature of yield of composition union and picture inpainting strategies utilizing little measure of unique information. Intra piece expectation and connection based number juggling coding in H.264, attempt to endeavor a few redundancies which are not abused by DCT alone, but rather these still work on an exceptionally nearby level and neglect to adventure redundacies at more worldwide level. Despite the fact that, building a pragmatic video codec in view of these standards would require more research exertion, present work is expected to be a little stride in that course. Our approach is similar to which uses non-parametric texture synthesis approach for image inpainting with appropriate choice of fill order. The contribution of present work is twofold. First, extend the work to three dimensions, which is more natural setting for video. Second, we extend the work which allows to use FFT based SSD calculation for all possible translations of a rectangular patch, to arbitrary shaped regions, thus making it applicable to image inpainting..

The paper is presented as follows. The Section II defines the Texture Synthesis. The Image inpainting is described in Section III and Section IV describes the methodology and section V presents the result and discussion. The conclusion of the paper is presented in last Section VI.

#### II. TEXTURE SYNTHESIS

Texture Synthesis has been utilized as a part of the writing to fill vast picture districts with composition design like given specimen [7]. Techniques utilized for this reason range from parametric, which gauge parameterized model for the composition and use it for union, e.g. Heeger et al., to nonparametric, in which combination depends on direct inspecting of the supplied composition design, e.g. Efros and Leung. Surface combination techniques have additionally been utilized to fill in little gaps in the picture which may start because of weakening of picture or craving to expel a few articles. But, aforementioned texture synthesis methods have been found to work poorly for highly structured textures which are common in natural images. Graph cut based strategies attempt to keep up auxiliary coherence amid surface combination by finding ideal crease while duplicating composition patches from various bits of picture.

### III. **I**MAGE INPAINTING

Image inpainting has been utilized as a part of the writing to fill in little openings in the picture, by proliferating structure data from picture to the district to be filled. Ordinarily, dissemination is utilized to proliferate straight structure in view of fractional differential condition. These are found to perform well in filling little gaps yet create discernible obscure when filling huge gaps. Recently, Criminisi et al. proposed a strategy which joins the advantage gave by surface amalgamation and picture inpainting. The results of their algorithm compare favorably with other state of the art in the field without resorting to texture segmentation or explicit structure propagation and are able to fill in large holes [6]. This paper presents similar approach to their work but this paper investigate some issues which are not so important for static images but become relevant for videos.

#### IV. METHODOLOGY

In inpainting technique 'I' represents the original image. ' $\Omega$ ' represents the target region, i.e. the region to be inpainted. ' $\Phi$ ' represents the source region, i.e. the region from which information is available to reconstruct the image. Generally,  $\Phi$  =  $I-\Omega.$  Also, we use ' $\delta\Omega$ ' to represent the boundary of the target region, i.e. the fill front. It is from here that we find some patch that is to be filled.

# An exemplar based inpainting algorithm involves the following steps:

1. Initialize the target region. This is generally performed separately from the inpainting process and requires the use of

an additional image processing tool. This is performed by marking the target region in some special color. Without any loss of generality, consider the color that the target region will be marked in is green (i.e. R = 0, G = 255, B = 0).

- 2. Find the boundary of the target region.
- 3. Select a patch from the region to be inpainted. The patch size should be a bit larger than the largest distinguishable texture element in the image. The default patch size  $9 \times 9$  can be changed with the knowledge of the largest texture element in the image. The patch is denoted by  $\psi p$ .
- 4. Find a patch from the image which best matches the selected patch,  $\psi p$ . This matching can be done using a suitable error metric. The Mean Squared Error is used to find the best matching patch.
- **5**. Update the image information according to the patch found in the previous step.
- (a) Extract pixel information from selected region First, select the image which is to be inpainted. Then (manually) select the region to be inpainted. The pixel values are extracted with minimum and maximum mean square error.
- (b) Selected region is to inpaint in the image is selected manually.
- (c) Select the incorrect patch may not produce the most visually plausible result.

Flowchart of the proposed system is shown in Fig.1

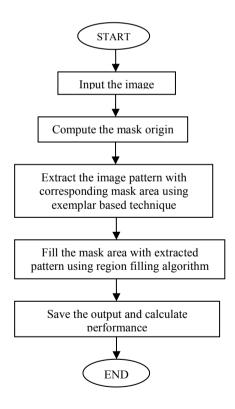


Fig.1: Flow chart of the Proposed system

#### V. **R**ESULT AND DISCUSSION

The performance of the system is evaluated on colored images in PNG format using exemplar based image inpainting technique. The comparison between existing method [1][3] and proposed method is based on three parameters MSE, PSNR and Time and it is observed that the proposed method improves these parameter values.

Table I: Comparison of the Existing[3] and Proposed system on the basis of Time parameter

| Image<br>name     | Image<br>size | Input<br>image | Mask   | Total<br>pixels | Damaged<br>Pixels | Existing<br>method<br>Time<br>(sec) | Proposed<br>method<br>Time<br>(sec) |
|-------------------|---------------|----------------|--|-----------------|-------------------|-------------------------------------|-------------------------------------|
| Building<br>image | 142×216       |                |  | 30672           | 3072              | 10.8910                             | 3.401                               |
| Grass<br>image    | 207×279       | No. of         |  | 37753           | 9516              | 46.4060                             | 21.232                              |
| Nature<br>image   | 257×386       |                |  | 99202           | 1833              | 61.4530                             | 16.193                              |
| Light<br>image    | 162×215       |                |  | 34830           | 1893              | 8.9530                              | 2.433                               |
| Man<br>image      | 257×342       |                | THE STATE OF THE S | 87894           | 9525              | 108.672                             | 31.917                              |
| Sea<br>image      | 220×176       | 18.00          | The state of the s | 38720           | 1125              | 7.2030                              | 1.716                               |
| Bird<br>image     | 199×257       | M              | M  | 51143           | 819               | 32.5630                             | 1.841                               |

The table I represents the comparison of the existing [3] and proposed system on the basis of damaged pixels of the image. Both systems are compared on the basis of time for the same number of damaged pixels. The images are given along with their size, total pixels, total number of damaged pixels and total time required by the existing system[3] and proposed system. The average time of existing method is 39.44 sec and average time of proposed system is 11.24 sec. The proposed system requires comparatively lesser time.

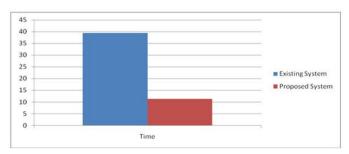


Fig.2: Comparison of Existing[3] and Proposed system for time parameter

The Fig.2 shows the comparison of the proposed system and existing system[3] on the basis of time parameter. It is shown that average value for the existing system is 39.44 sec and that of proposed system is 11.24 sec.

Table II: Comparison of the Existing[1] and Proposed system on the basis of MSE values

| Image<br>Name | Input<br>Image | Mask | Image<br>Size | Damaged<br>Pixels | Using<br>NCC<br>MSE | Using<br>SSD<br>MSE | Using<br>Hamming<br>MSE | Proposed<br>Method<br>MSE |
|---------------|----------------|------|---------------|-------------------|---------------------|---------------------|-------------------------|---------------------------|
| Grid          |                |      | 121×121       | 294               | 0                   | 0.55                | 0.57                    | 0.307                     |
| Synth etic    |                | 11   | 63×64         | 312               | 0                   | 0.001               | 0.001                   | 0                         |
| Came<br>raman |                |      | 160×160       | 246               | 0.33                | 0.26                | 0.42                    | 0.33                      |
| Cat           |                |      | 209×176       | 480               | 0.33                | 0.43                | 0.49                    | 0.25                      |

The table II represents the comparison of the existing[1] and proposed system on the basis of damaged pixels of the image. Both systems are compared on the basis of MSE for the same number of damaged pixels. Various images are given along with their size, total pixels, total number of damaged pixels, MSE required by the existing system and proposed system. The proposed system has lower MSE values than that of existing system[1] that shows better performance of the proposed system over existing system.

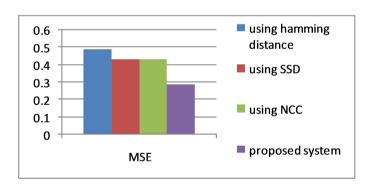


Fig.3: Comparison of Existing[1] and Proposed system for MSE Parameter

The fig.3 shows the comparison of the proposed system and existing system[1] on the basis of MSE parameter. The average value of MSE using the hamming distance is 0.49, average value of MSE using SSD is 0.43, average value of MSE using NCC is 0.43 and that of proposed system is 0.29.

Table III: Comparison of the Existing[1] and Proposed system on the basis of PSNR parameter

| Image<br>Name | Input<br>Image | Mask | Image<br>Size | Damaged<br>Pixels | Using<br>NCC<br>PSNR | Using<br>SSD<br>PSNR | Using<br>Hamming<br>distance<br>PSNR | Proposed<br>Method<br>PSNR |
|---------------|----------------|------|---------------|-------------------|----------------------|----------------------|--------------------------------------|----------------------------|
| Grid          |                |      | 121×121       | 294               | Infinity             | 101.33               | 101.71                               | 111.826                    |
| Synthetic     |                | 11   | 63×64         | 312               | infinity             | Near to infinity     | Near to infinity                     | infinity                   |
| Cameram<br>an |                |      | 160×160       | 246               | 101.65               | 107.92               | 103.77                               | 111.05                     |
| Cat           |                |      | 209×176       | 480               | 101.65               | 103.41               | 102.11                               | 113.65                     |

The table III represents the comparison of the existing[1] and proposed system on the basis of damaged pixels of the image. Both systems are compared on the basis of PSNR for the same number of damaged pixels. The images are given along with their size, total pixels, total number of damaged pixels, PSNR required by the existing system and proposed system. It is also concluded that proposed system has higher PSNR values than that of existing system[1] that depicts the better performance of the proposed system over existing system[1].

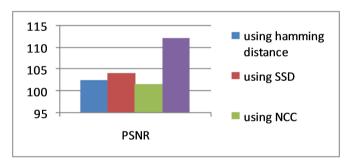


Fig.4: Comparison of Existing[1] and Proposed system for PSNR Parameter

The fig.4 shows the comparison of the proposed system and existing system[1] on the basis of PSNR parameter. The average value of PSNR using hamming distance system is 102.53, average value of PSNR using SSD is 104.22, average value of PSNR using NCC is 101.65 and that of proposed system is 112.17.

## VII. CONCLUSION

The proposed system is developed to inpaint the colored images. Exemplar based inpainting technique is implemented to inpaint or restoration of images. In this paper, pattern

extraction technique is used to find the best matching patch. The performance of the proposed system is evaluated on real world images as well as standard data collected from various sources. Experimental results shows that the proposed system results are better as compare to existing system [1][3]. The proposed system is compared on the basis of parameters Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and time.

In future, PSNR and MSE of images can be increased and time can be decreased by doing further enhancement in this pattern extraction technique.

#### REFERENCES

- Chetan Ralekar, Shweta Dhondse and M. M. Mushrif, "Image Reconstruction by Modified Exemplar Based Inpainting", IEEE pp.1005-1010, 2015.
- [2] Manoj S Ishi, "Exemplar based Inpainting using Wavelet Transform", International Journal For Technological Research In Engineering, Vol. 2 [5], pp.463-466, 2015.
- [3] Waykule J.M., "Modified Image Exemplar-Based Inpainting", International Journal of Advanced Research in Computer and Communication Engineering ,Vol. 2 [9], pp.3734-3740, 2013.
- [4] Bhimaraju Swati, Naveen Malviya, Shrikant Lade, "Analysis of Exampler Base Inpainting for Adaptive Patch Propagation using Wavelet Transform" International Journal of Emerging Technology and Advanced Engineering, Vol. 3[5], pp.749-756, 2013.
- [5] Yogita More, Savita Tuplondhe, Dhanashree More and Ashwin Patil, "Image Inpainting Using Exemplar Based Method and Multiscale Graph Cuts", International Journal of Research in Advent Technology, pp.256-260, Vol.2[4], 2014.
- [6] A. Criminisi, P. Perez, and K. Toyama, "Region filling and object removable examplar- based image inpainting", IEEE Trans. Image Process., vol. 13, pp. 1200–1212, 2004.
- [7] M. Bertalmio, L. Vese, G. Sapiro, and S. Osher, "Simultaneous Structure and Texture Image Inpainting" IEEE Transactions On Image Processing, Vol. 12, No. 8, pp.882-889, 2003.
- [8] Kaushikkumar R. Patel, Lalit Jain, and Ankurkumar G.Patel, "Image Inpainting – A Review of the Underlying Different Algorithms and Comparative Study of the Inpainting Techniques", International Journal of Computer Applications, Vol. 118 – No. 10, pp.32-38, 2015.
- [9] Abhijit L. Rakshase, S. N. Gite, "Exemplar Based Super-Resolution Technique for Image Inpainting: A Review", International Journal of Advanced Research in Computer and Communication Engineering, Vol.4 [5], pp.74-76, 2015.
- [10] Jaspreet Kaur Chhabra, Vijay Birchha, "An Enhanced Technique for Exemplar based Image Inpainting", International Journal of Computer Applications, Vol. 115 [17], pp.20-25, 2015.
- [11] M. Bertalmio, G. Sapiro, V. Caselles, "Image inpainting, in proceedings of ACM SIGGRAPH Conference on Computer Graphics", Vol.35[4], pp. 417-424, 2000.