AIVP ADVANCES IN IMAGE AND VIDEO PROCESSING

SOCIETY FOR SCIENCE AND EDUCATION UNITED KINGDOM

VOLUME 2, ISSUE 1
ISSN: 2054 - 7412

Laplacian Pyramid based Hierarchical Image Inpainting

[1]S. Padmavathi, [2]K. P. Soman
[1] Department of Information Technology
[2]Head of CEN department
Amrita School of Engineering, Coimbatore, India.
[1]s_padmavathi@cb.amrita.edu, [2] kp_soman@amrita.edu

ABSTRACT

There are many real world scenarios where a portion of the image is damaged or lost. Restoring such an image without prior knowledge or a reference image is a difficult task. Image inpainting is a method that focuses on reconstructing the damaged or missing portion of images based on the information available from undamaged areas of the same image. The existing methods fill the missing area from the boundary. Their performance varies while reconstructing the structure and texture present in the image and majorly fails for larger inpainting area. This paper attempts to segregate the structure and texture using Laplacian Pyramid and inpaint them separately using a top down approach. The images are inpainted from the lowest spatial resolution using Exemplar based image synthesis. The results are updated before moving to the higher resolution levels. This multi resolution process ensures the coarser details being filled before the finer details. The structure propagation is better since it is handled separately. The top down approach alleviates the traditional boundary based filling and breaks the single large sized inpainting region into many smaller sized ones as we move down the pyramid. Different types of images have been experimented and the results are summarized.

Keywords: Hierarchical Digital Image Inpainting, Laplacian Pyramid, Exemplar based Inpainting, Multiresolution Inpainting

1. INTRODUCTION

In olden days, artists reconstructed the damaged paintings by propagating the colors in the boundary of damaged parts. This process was known as inpainting. Bertalmio et al [10] used a digital version of the technique to restore cracks in photos and to remove inscribed texts on digital images and called it as Digital image Inpainting. In general, the term image inpainting refers to the synthesis of the damaged, missing or hidden portion of the image in a visually plausible way. Inpainting is used in a primitive form in certain image editing software. They expect the user to specify the area to be inpainted and also specify the sample that has to be put in its place. Digital image inpainting requires the user to specify the area to be inpainted,

DOI: 10.14738/aivp.21.46
Publication Date:10th February 2014
URL: http://dx.doi.org/10.14738/aivp.21.46

but fills it automatically using the information available in the surrounding area of the same image. The inpainting problem is also addressed under disocclusion, object removal etc. The applications of inpainting includes removal of cracks from a damaged photograph, retrieving the damaged portions of digital paintings, removing unwanted texts and objects in a scenic photograph, removing the obstacles and retrieving the hidden background, removing the objects to create special effect etc.

The propagation of the information into the inpainted area determines the success of the algorithm. The geometric and the photometric propagation which is generally called as structure and texture propagation poses a major challenge to inpainting algorithms. Partial differential equations based inpainting algorithms perform well for smaller inpainting areas. Texture synthesis based methods work well for larger areas but fail in geometric propagation. Exemplar based methods which is a kind of texture synthesis technique performs reasonably well for larger areas but fails in structure propagation at a larger scale. The technique presented in this paper is inspired by the response of Human visual system in viewing a photograph from various distances. When viewed from a larger distance only the coarser information in the image could be viewed. As the distance reduces the finer details could be seen. Hence filling in the coarser information and then the finer information will result in better reconstruction. The Phenomenon is best imitated by the image pyramid discussed by Burt and Adelson in [1], with the image viewed from farthest distance at the top of the pyramid and the image viewed at the closest distance at the bottom of the pyramid. In general the actual image forms the bottom and its smoothened version, forms the higher levels in the Gaussian pyramid. The spatial resolution reduces as we move up in the pyramid. This paper follows a top down multi resolution approach for filling the inpainting area which means the images are inpainted from the topmost level to the original image at the bottom of the pyramid. Since Gaussian pyramids do not preserve the structural information between the levels, Laplacian pyramids are considered. Laplacian pyramid is capable of synthesizing the original image from the top most images without any error. Apart from this it also segregates the structural information at each level. The technique in this paper utilizes the patch based Exemplar method as discussed by Crimsini et al in [25] which assigns priorities for pixel and reconstructs from the boundary looking for similar patches from the undamaged area. The nature of the pyramid together with the top down approach inherently reduces the inpainting area into many smaller regions at successive levels. This in turn enhances the performance of the algorithm. The paper is organized with the state of art in section II, the detailed discussion of the proposed method in section III, the experimentation and result in section IV and conclusion in section V.

2. STATE OF THE ART

In inpainting terminology, missing area or the damaged area is called as Ω, the known or undamaged area is termed as source Φ and the boundary between them is termed as $\delta\Omega$ as shown in fig. 1. The Ω will be specified as an input to the algorithm in the form of a binary image called the mask. The inpainting algorithm should assign appropriate gray levels to the Ω such that it blends with the remaining image. The boundary δΩ, plays a major role in deciding the intensities in Ω. The existing inpainting algorithms are iterative and try to fill in the area near the δΩ until a criterion is reached.

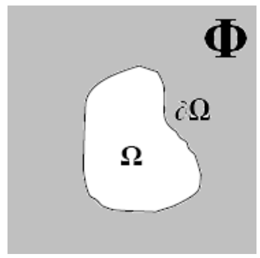


Fig.1. Digital image Inpainting problem

Interpolation methods [4],[7] are the primitive methods which can be used for inpainting. In the interpolation method, the neighboring pixels are considered for filling the inpainting area. The technique gives better result for the uniform area and fails in high structured regions. Bertalmio et al. [12], [18] used a digital image inpainting algorithm based on partial differential equations (PDEs). Anisotropic diffusion[2] is applied to extent the isophote lines. Though the algorithm works well for small textured images, it fails in large textured images. The mathematical models for variational PDE are explained in detail in [22]. In [13] a convolution mask is used to extend the gray levels in to the inpainting area. The curvatures are extended into the inpainting area in [14]. Level line based inpainting is discussed in [20]. Other methods involving partial differential equation and concentrating on smaller structures could be found in [10] and [23].

Texture based methods could be used for synthesizing images [8]. Various texture synthesis methods could be found from [9],[15],[16] and [19]. These methods grow a new image outward from an initial seed. Pyramid based texture synthesis are discussed in [3] and [6]. Texture synthesis based inpainting are used in [5] and [24]. Exemplar based technique for filling image regions are dealt in [17] and [25]. It is derived from patch based texture synthesis. The algorithm works by taking a patch around a pixel on the boundary and replacing it with the best patch found by searching in the source region. In [25] both structure and texture information is propagated into the mask region. Inpainting in a video sequence is discussed in [21] and fractal based method is discussed in [26].

A comparative analysis of structure and texture based methods is discussed in [27]. A hierarchical model using TV method is discussed in [28] which reproduces the general texture for a large mask but fails in reproducing finer details. A hierarchical model using wavelets is discussed in [30], though it reproduces the texture appropriately, it increases the overhead of inpainting in the four components for each level. A hierarchical exemplar based model is discussed in [29]. Hierarchical filling performs better in reproducing the structure and texture but results in distortion due simple subsampling process. The advantage of hierarchical filling is used in this paper in an efficient way by segregating structure and texture with an overhead much less when compared to Wavelet based method.

3. INPAINTING USING LAPLACIAN PYRAMID

Image pyramids are suitable for multi resolution image processing. The general structure of image pyramid is shown in Fig.2 with the image of size *N* x *N*, at the base of the pyramid. The lower resolution images forms the higher layers of pyramid and the lowest resolution image at the apex. Generating the pyramid from the bottom is called as decomposition while generating from the top is called as synthesis. For hierarchical inpainting, the image and the area to be inpainted is represented at different resolution levels. The Inpainting algorithm is applied in a top down manner starting from the apex of the pyramid; the results are updated in the layer immediately below it. This process continues until the base image is inpainted. Usually the inpainting process uses only few layers from the base depending on the mask size.

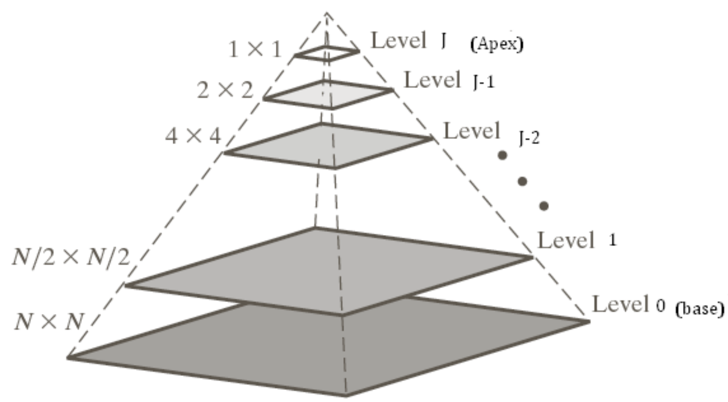


Fig.2. Image Pyramid

The main success of inpainting algorithm relies on the segregation of the structure and texture. A blurring process reduces the structural information in an image. When a sampling process is done on it, it forms the layers of a Gaussian pyramid. The difference of blurred version and the image is expected to give the structural information. This is generally called as the Laplacian. The loss of data between the levels should be minimal to avoid the additional error incurred by the sampling. Separating the structure from the texture and handling them individually improves the quality of the inpainting algorithm. These requirements makes the Laplacian pyramid a better choice. The Laplacian pyramid has the Gaussian image at the apex and the Laplacian images at other layers. Inpainting in Laplacian pyramid is carried out in two different ways depending on the Gaussian used for synthesizing. Another method using Gaussian and Laplacian at each level is also experimented.

3.1 Inpainting With One Gaussian

In the first method the image is blurred level number of times (say 'j') and each time it is down sampled and subtracted from the unblurred version to get the Laplacian. Finally the pyramid consists of Laplacian images with size varying from N x N at level 0 to $N/2^j$ x $N/2^j$ at level 'j'. It has a Gaussian image which is blurred 'j' times and is of size N x N. The mask pixels are extracted and maintained separately for each level. Inpainting algorithm is applied to the topmost Laplacian and the results are updated in the layer below. The algorithm stops after inpainting the Gaussian once and adding it to the base Laplacian.

In the second method, formation of the Laplacian pyramid remains the same as described before, but the Gaussian in this case is a single blurred version of the original image. Hence the pyramid consists of Laplacian images with size varying from N x N at level 0 to $N/2^j$ x $N/2^j$ at level 'j' and a Gaussian image which is blurred once and is of size N x N. Inpainting algorithm is similar to the previous method. Both the method described above introduces additional cost of inpainting the Laplacians at each level. Since the inpainting is done in a top down manner and the pixels inpainted at higher levels of pyramid are not repainted in the lower levels, the computational cost incurred due to multi resolution processing is thus reduced effectively. Moreover updating lower levels with the inpainted results of the higher level provides more interior pixel effectively breaking down the single large sized mask into many smaller sized ones. Many inpainting algorithms are efficient for smaller sized masks.

3.2 Inpainting With Multiple Gaussian

In this method the Gaussian and the Laplacian at each level is maintained in the pyramid. Hence the pyramid consists of 'j+1' Laplacian and 'j+1' Gaussian images. The images at the 'j^{th}' level of the pyramid is of size $N/2^j$ x $N/2^j$. The algorithm inpaints top most layer of Gaussian and the Laplacian. The result of the Laplacian is updated to the layer below while their combined results are used to update the Gaussian in the layer below. The algorithm proceeds until the base level. This inpainting cost doubles when compared to the previous method, but the combination of structure and texture at each level result in better reconstruction.

3.3 Inpainting Algorithm

At each level of the pyramid Exemplar based inpainting is applied to the mask pixels. In this method a sub window called patch (ψ_p) centered on a pixel 'p' at $\delta\Omega$ is chosen for inpainting. This sub window encompasses certain pixels from Φ and certain other pixels from Ω. The source region (Φ) is queried for similar pixels as that of known pixels in the sub window. The closest match provides the values for the unknown pixels in the patch. The Boundary $\delta\Omega$ and the mask pixels Ω are updated and the process continues until all mask pixels are assigned values. The process of Exemplar based inpainting is illustrated in Fig. 3. The selection of patches plays a crucial role in the quality of inpainting. The presence of more known pixels and the patch centered on a structure are primary concern in the selection process. The Confidence term C(p) and the Data term D(p), as coined by Crimsini et al[25]. are used for this purpose.

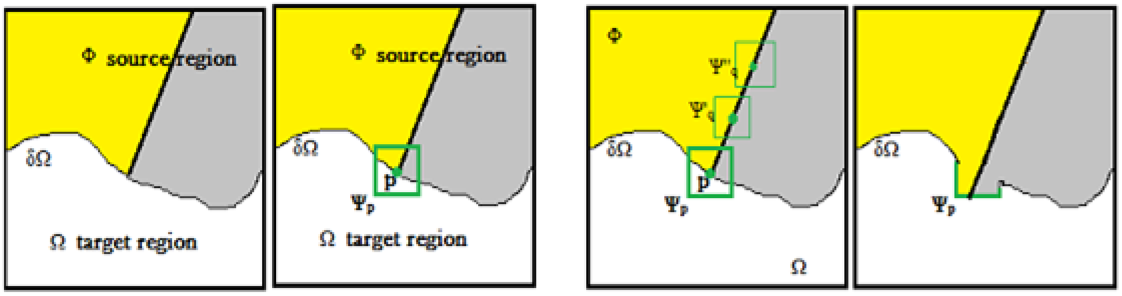


Fig.3. Exemplar based Inpainting

The algorithm for Laplacian pyramid based hierarchical inpainting is as follows:

1. Accept the area to be inpainted(mask) from the user through color, area selection or mask file
2. Generate the Pyramid as specified in section 3.1 and 3.2
3. Compute the mask pixels at each layer.
4. Initialize the confidence term for the mask pixels to zero.
5. Compute the priority of the patches of the top most layer as given by Eqn (1)

$$P(p) = C(p) * D(p) \tag{1}$$

Where C(p) and D(p) refers to the confidence term and data term of the patch (ψ_p) centered at pixel 'p'. They are calculated using Eqn(2) and Eqn(3) respectively

$$C(p) = \frac{\sum_{q \in \psi_p \cap \Omega} C(q)}{|\psi_p|} \tag{2}$$

Where $|\psi_p|$ is the cardinality of the patch.

$$D(p) = \frac{|\nabla p^{\perp} .np|}{\alpha} \tag{3}$$

Where $\nabla p^{\perp}$ is the isophote which is orthogonal to the gradient ∇p , α is the normalization factor, np is the normal vector to the contour δΩ at p

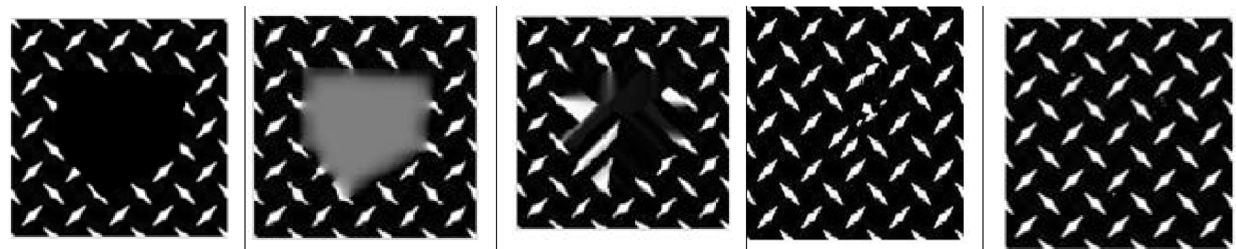
6. Choose the patch Ψp with the maximum priority as in equation (4),

$$p = arg\ max\ p\ for\ all\ P(p) \tag{4}$$

7. Find the best matching patch Ψq Є Φ in source region that minimizes d(Ψ p*;* Ψ q), where d is the Sum of Squared Distance(SSD).
8. Copy image data from Ψ q to Ψ p for all pixels belonging to the target region **Ω**.
9. Update *C*(p) and the D(p) for the newly filled pixels.
10. Repeat steps 5 to 9 until all target pixels in the current level are filled.
11. Update the pixel values in the layer below and update the mask pixels.
12. Repeat step 4 to 11 until the base of the pyramid is inpainted.

4. EXPERIMENTAL RESULTS

Images consisting of different textures and structures are considered for experimentation. Isotropic diffusion based methods perform well in smooth areas; anisotropic diffusion based methods and Partial differential equation based method perform well for smaller inpainting regions but fail for larger inpainting area. Texture synthesis based methods perform well for larger regions but fails to propagate the structure. Exemplar based method performs well in natural images but fails in larger structure propagation. The performance of inpainting with multiple Laplacian and Gaussian is compared with the existing method for a textured image in Fig 4. The left most image represents the image with a large mask and the results of anisotropic diffusion method, Total variation method, exemplar based method and the proposed method are listed to its right in the order specified.



(a)Image with mask	(b)Anisotropic diffusion	(c)Total variation	(d)Exemplar	(e) Multiple Laplacian

Fig. 4 : Comparison with existing methods

The result of exemplar based method on a natural image is shown in Fig. 5a. A similar image with the mask area in white color is shown in Fig 5b. The result of a hierarchically inpainted image is shown in Fig 5c. The result of inpainting using Gaussian pyramid upto 2 levels is shown in Fig.6. The image with mask and the inpainted result from first and second level are shown in the order from left to right.

(a). Exemplar based method	(b). Similar image with mask	(c). Hierarchically inpainted

Fig. 5 : Comparison of exemplar method with hierarchical method

It is clear from the picture that its performance drops as we move up in the pyramid. The method using single Gaussian had varied response among different images. When the Gaussian that is blurred j times and all the Laplacians were used, the images with linear structures were not constructed properly, the overall texture construction was better. It also reduced the sharpness in a reconstructed image. The results on various images are shown in Fig 7(a) through (e). When all the Laplacians and the original image was used for inpainting the blurring was avoided but the overall reconstruction in a textured image was not upto the mark. Some of the results on similar images are shown in Fig 8 (a) through (e).

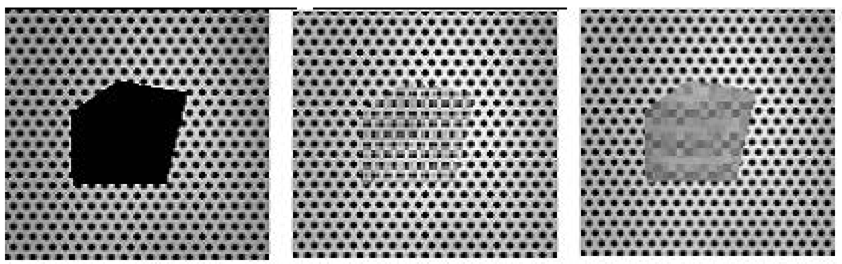
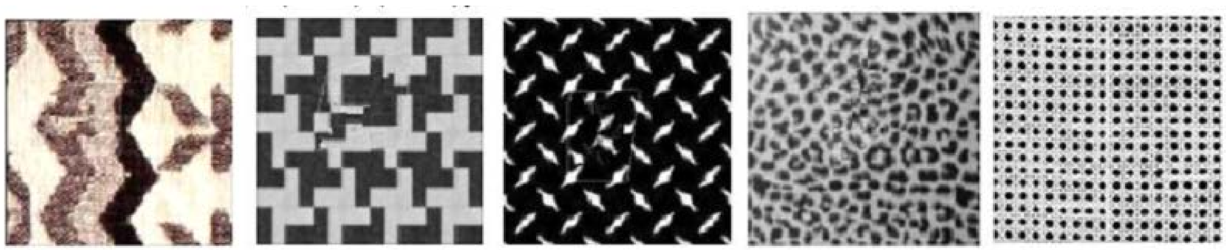
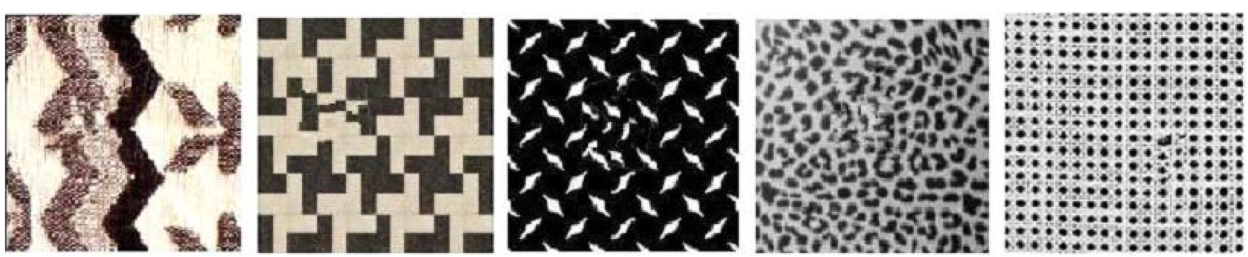


Fig. 6 : Inpainting with Gaussian Pyramid



(a) (b) (c) (d) (e)

Fig. 7(a)-(e) : Inpainting using single Gaussian (blurred)



(a) (b) (c) (d) (e)

Fig.8(a)-(e) : Inpainting using single Gaussian (Original)

When the Laplacian and Gaussian at each level are inpainted separately and their combined results were updated to the lower level in the pyramid, the structure and texture reconstruction was better. The result of Inpainting the Laplacian and Gaussian at each level for an image is shown in Fig 9. The area is selected by the user for inpainting. The number of levels were fixed as 3 for this case. The Gaussian and Laplacian are inpainted at level three and given as input to level 2, where some portions are inpainted and given to level 1 as illustrated in

Fig.10. Though the images are of different size they are shown in same scale for ease of comparison.

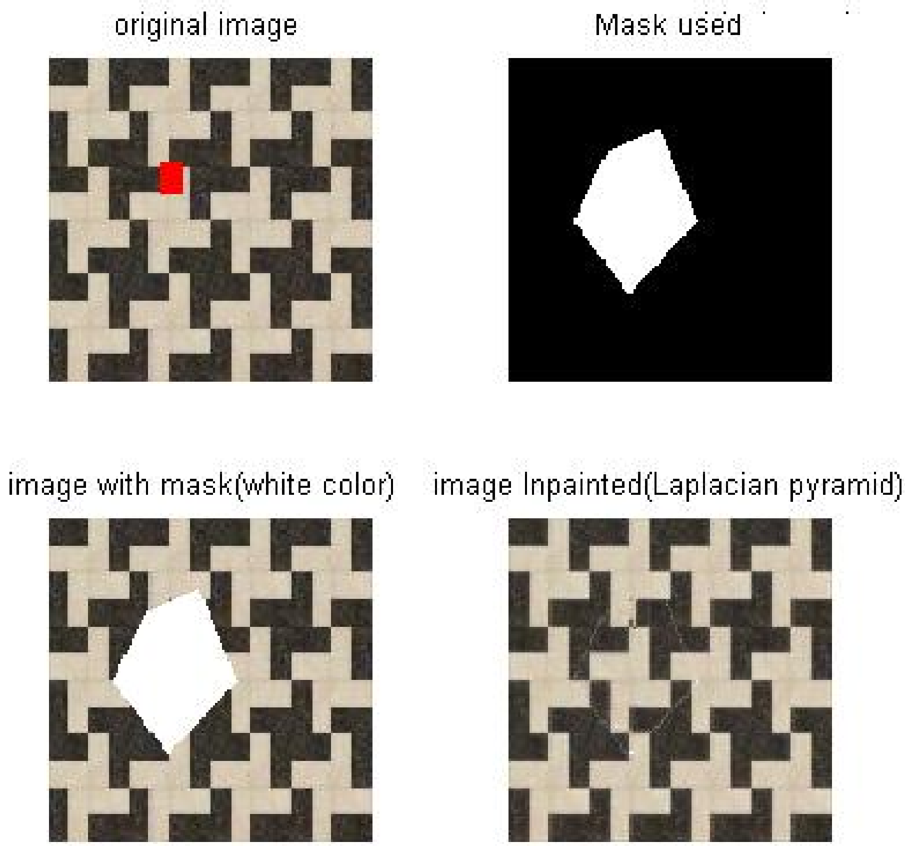


Fig.9 : Inpainting using multiple Gaussian

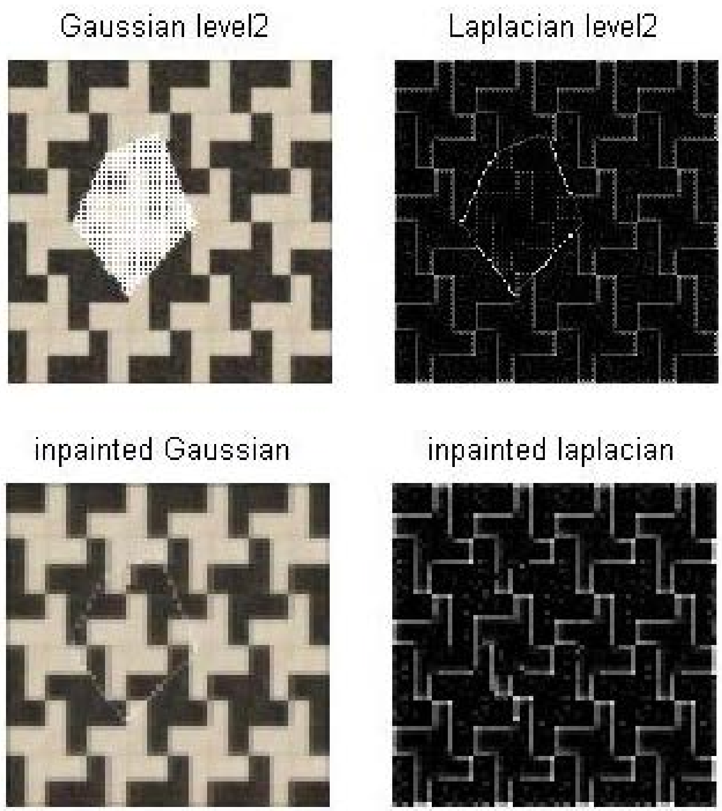
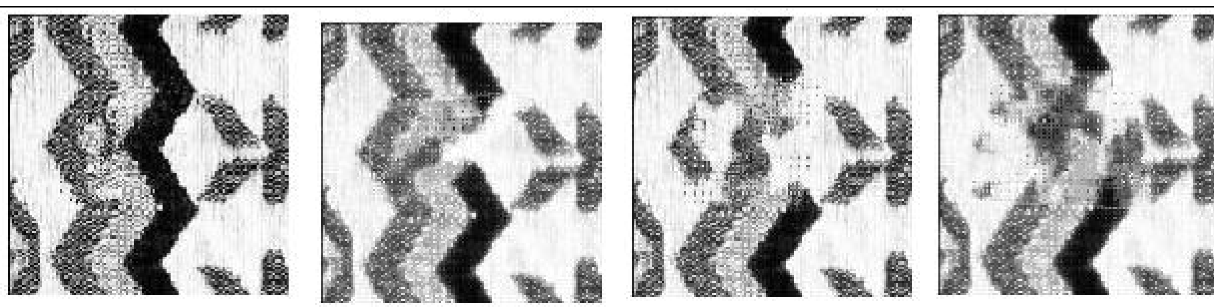


Fig. 10 : Inpainting using multiple Gaussian atLevel 2

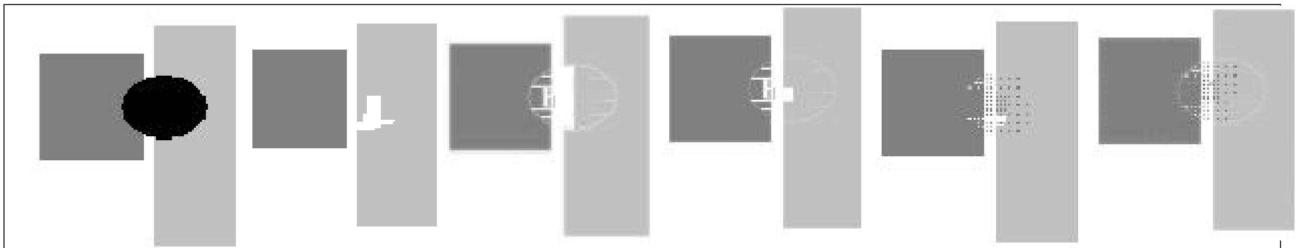
The Size and the spread of the Gaussian filter used for generating the pyramid also contributes to the quality of the reconstructed image. The reconstructed images with various window sizes and spreads are shown in Fig. 11. The reconstructed image with window size 5x5 and spread of 0.3 is shown in Fig.11a; window size 5x5 and spread 0.9 in Fig11b; window size 9x9 and spread 0.5 in Fig11c and window size 9x9 and spread 0.9 in Fig11d.



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

Fig. 11 (a)-(d): Inpainted images with various window size and Spread

As the spread increases the blurring in the reconstructed image also increases. When the window size increases the larger structures are reconstructed properly but it may introduce noisy textures whose visibility is less in a natural scenary images but is clearly visible in fixed shape images. Smaller window sizes degrades the structure reconstruction and also introduces the noisy textures in fixed shape images. The Choice of the window size is majorly influenced by the nature of the image. For the test data that has been considered a spread of 0.5 and a window size of 5x5 gave good results. The number of levels used for inpainting is influenced by the size of the area to be inpainted. Inpainting upto level 3 proved sufficient for the data set. The rectangular patch being considered affects the all exemplar based inpainting while inpainting curved areas. The effects are predominant for images with few fixed shapes and colors. The result of inpainting an oval area is shown in Fig 12 (b)-(f). The original image with the area to be inpainted indicated in black is shown in Fig12(a). The inpainted image using Exemplar based method, Laplacian pyramid with blurred Gaussian, Laplacian pyramid with unblurred Gaussian, Laplacian pyramid with multiple Gaussians with 5x5 window size, 0.3 spread and 9x9 window size, 0.5 spread is shown in Fig 12 (b),(c),(d),(e) and (f) respectively.



(a) (b) (c) (d) (e) (f)

Fig. 12 (b)-(f): Exemplar based Inpainted images for Oval area shown in (a)

5. CONCLUSION

Inpainting an image requires the proper reconstruction of the structures and textures. Parital Differential equation based methods fail for larger inpainting areas. Texture synthesis based methods does not guarantee the completion of structures. The existing exemplar based algorithms fail in reconstructing larger structure and depends on the boundary pixels for filling the regions. The error occurring in the initial stage percolates to the interior regions. When inpainted using a Laplacian pyramid the structural and textural information are handled separately. Inpainting in a top down manner reduces the mask size at successive levels giving more known interior pixels which increases the performance of the Exemplar based method. A combination of structure and texture at each level is required for a perfect reconstruction though it consumes more time than inpainting the laplacians and a single Gaussian. The window size and the spread of the filter and the number of levels in the pyramid affect the inpainting quality and the computational cost. The choice of these parameters is influenced by the nature of the image and the size of the mask. The Laplacian pyramid based inpainting introduces noise at lower pyramids when the mask area is oval and when the image has few definite shapes. Exemplar based methods are limited in synthesizing the image portions that are existing in the surrounding and do not generate any new patterns.

REFERENCES

[1]. P.J. BURT, E. H. ADELSON.,"The Laplacian Pyramid as a Compact Image Code"., IEEE Trans on Communication,vol. COM-31, no. 4, April 1983

[2]. P. PERONA AND J. MALIK, Scale-Space Edge Detection Using Anisotropic Diffusion, *IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No.7, July 1990,* http://www.cs.berkeley.edu/~malik/papers/MP-aniso.pdf

[3]. D.J. HEEGER AND J.R. BERGEN, Pyramid-Based Texture Analysis/Synthesis, *Proceedings of SIGGRAPH 1995, pp 229-238, September 1995.*http://www.cns.nyu.edu/~david/ftp/reprints/heeger-siggraph95.pdf

[4]. A.C. KOKARAM, R.D. MORRIS, W.J. FITZGERALD AND P.J.W. RAYNER, “Interpolation of Missing Data in Image Sequences”,IEEE Transactions on Image Processing. Vol. 4. No.11, Nov. 1995, pp 1509-1519. URL: http://www.robinmorris.org/sigproc/interpolation.pdf

[5]. H. IGEHY AND L. PEREIRA, “Image Replacement through Texture Synthesis”,Proceedings of the IEEE International Conference on Image Processing, October 1997.URL: http://graphics.stanford.edu/papers/texture_replace/texture_replace.pdf

[6]. J.S. DE BONET, “Multi resolution sampling procedure for analysis and synthesis of texture images”, in Proc. ACM Conference Computer Graphics (SIGGRAPH), volume 31, pages 361–368, 1997.

[7]. V. CASELLES, J. M. MOREL, AND C. SBERT, "An Axiomatic Approach to Image Interpolation", IEEE Transactions on Image Processing, 7, Issue 3, Mar 1998, Page(s): 376 - 386.

[8]. M. TUCERYAN AND A. K. JAIN, “Texture Analysis,” Handbook of Pattern Recognition and Computer Vision, C. H. Chan, L. F. Pau, and P. S. P. Wang (Eds.), Ch.2, pp. 235-276, Singapore: World Scientific, 1998.

[9]. A. EFROS AND T. LEUNG. Texture synthesis by non-parametric sampling.In *Proc. Int. Conf. Computer Vision*, pages 1033–1038, Kerkyra, Greece, September 1999.

[10]. M. BERTALMIO, G. SAPIRO, V. CASELLES, AND C. BALLESTER, "Image Inpainting" Proceedings of the ACM SIGGRAPH Conference on Computer Graphics, SIGGRAPH2000, New Orleans, USA. July 2000, pp 417-424. URL: http://www.iua.upf.es/~mbertalmio/bertalmi.pdf

[11]. M. BERTALMIO, A.L. BERTOZZI AND G. SAPIRO, “Navier-Stokes, Fluid Dynamics, and Image and Video Inpainting”, Proc. IEEE Computer Vision and Pattern Recognition (CVPR’01), Hawaii, December 2001. http://www.iua.upf.es/~mbertalmio/final-cvpr.pdf

[12]. BALLESTER, M. BERTALMIO, V. CASELLES, G. SAPIRO, AND J. VERDERA, "Filling-in by Joint Interpolation of Vector Fields and Gray Levels", IEEE Transaction on Image Processing, 10, Issue 8, Aug 2001, Page(s): 1200 - 1211.

[13]. M.M. OLIVIEIRA, B. BOWEN, R. MCKENNA AND Y.S. CHUNG, “Fast Digital Image Inpainting”, Proceedings of the International Conference on Visualization, Imaging and Image Processing (VIIP 2001), Marbella, Spain 2001. Sep. 3-5, 2001, pp 261-266. URL: http://www.cs.sunysb.edu/~oliveira/pubs/inpainting.pdf

[14]. T. F. CHAN AND J. SHEN, "Non-Texture Inpainting by Curvature-Driven Diffusions (CDD)", Journal Visual Communication and Image Representation, 12, Number 4, 2001, Page(s): 436 - 449.

[15]. M. ASHIKHMIN. “Synthesizing natural textures”. In Proc. ACM Symposium on Interactive 3D Graphics, pages 217–226, Research Triangle Park, NC, March 2001.

[16]. A. EFROS and W.T. FREEMAN, “Image quilting for texture synthesis and transfer”. In Proc. ACM Conf. Comp. Graphics (SIGGRAPH), pages 341–346, Eugene Fiume, August 2001.

[17]. A. HERTZMANN, C. JACOBS, N. OLIVER, B. CURLESS, and D. SALESIN, “Image analogies”. In Proc. ACM Conf. Comp. Graphics (SIGGRAPH), Eugene Fiume, August 2001.

[18]. C. BALLESTER, V. CASELLES, J. VERDERA, M. BERTALMIO, and G. SAPIRO. “A variational model for filling-in gray level and color images”. In Proc. Int. Conf. Computer Vision, pages I: 10–16, Vancouver, Canada, June 2001.

[19]. P.Harrison, “A non-hierarchical procedure for re-synthesis of complex texture”, in Proc. Int. Conf. Central Europe Computer Graphics, Visualization And Computer Vision, Plzen, Czech Republic, February 2001.

[20]. S. MASNOU, "Disocclusion: A Variational Approach using Level Lines", IEEE Transactions on Signal Processing, 11, Issue 2, Feb 2002, Page(s): 68- 76.

[21]. R. BORNARD, E. LECAN, L. LABORELLI AND J-H. CHENOT, “Missing Data Correction in Still Images and Image Sequences”, ACM Multimedia 2002, Juan-les-Pins, France, Dec. 2002. URL: http://brava.ina.fr/papers/INA_Raphael_Bornard/RBornard_mm2002_preprint.pdf

[22]. T.F. CHAN, J. SHEN AND L. VESE, “Variational PDE Models in Image Processing”, UCLA Computational and Applied Mathematics Reports 02-61, Dec. 2002. URL: ftp://ftp.math.ucla.edu/pub/camreport/cam02-61.pdf

[23]. J. SHEN, “Inpainting and the Fundamental Problem of Image Processing”, SIAM News 36(5), June 2003. http://www.math.ucla.edu/~imagers/htmls/internalreport/ShenSIAM.pdf

[24]. M. BERTALMIO, L. VESE, G. SAPIRO AND S. OSHER, “Simultaneous Structure and Texture Image Inpainting”, in Proc. Conference Computer Vision Pattern Recognition, Madison, WI, 2003. Proceedings of the 2003 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’03), volume 2, June 2003. URL: http://www.math.ucla.edu/~lvese/PAPERS/01211536.pdf

[25]. A. CRIMINISI, P. PÉRES AND K. TOYAMA, "Region Filling and Object Removal by Exemplar-Based Image Inpainting"., IEEE Trans on Image Processing , vol. 13, NO. 9, sep 2004

[26]. I. DRORI, D. COHEN-OR AND H. YESHURUN, “Fragment-Based Image Completion”, ACM Transactions on Graphics (TOG), volume 22 issue 3, July 2003. URL: http://portal.acm.org

[27]. S.PADMAVATHI, K.P.SOMAN ,Comparative Analysis of Structure and Texture based Image Inpainting Techniques, International Journal of Electronics and Computer Science Engineering,(IJECSE)Volume 1, Number 3, June 2012, pp1062-1069

[28]. S.PADMAVATHI, N.ARCHANA, K.P.SOMAN , Hierarchical Approach For Total Variation Digital Image Inpainting, International Journal of Computer Science, Engineering and Applications (IJCSEA), Volume 2, number 3, june 2012, PP173-182

[29]. S.PADMAVATHI, K.P.SOMAN, A Hierarchical Search Space Refinement and filling for Exemplar based Image Inpainting, International Journal of Computer Applications (IJCA) Volume 52, number4, August 2012, pp31-37.

[30]. S.PADMAVATHI, B. PRIYA LAKSHMI, K.P.SOMAN, Hierarchical Digital Image Inpainting using Wavelets , Signal & Image Processing:An International Journal (SIPIJ),Volume 3, Number 4, August 2012, pp85-93.