IJCSC 0973-7391 Volume 7 • Number 1 Sept 2015 - March 2016 pp.117-128 available online at www.csjournalss.com

Hybrid Approach for Inpainting Large Object

Rajkumar L. Biradar
Associate Professor
Electronics & Telematics Department,
G. Narayanamma Institute of Technology & Science, Hyderabad, INDIA
rajkumar_lb@yahoo.com

Abstract: The manual repair of ancient artwork, paintings or photographs by professional and experienced experts is restoration. It is an art as well as science. The old photographs and artistic paintings are preserved for many years. While preserving, they are damaged due to age, dust, insect byte and develop scratches and cracks due to handling and folding. These damages are to be restored by either repairing or removing the damaged regions by suitable filling. Generally, from the knowledge of global information of painting, painter fills in the damaged region with appropriate colors and fine brushes such that the restored painting is almost original. Thus the practice of filling-in damaged region and making modifications to paintings in a non detectable way to an observer who looks at the restored work of art, without knowing the original damaged painting is called restoration. Instead of manual restoration, if we use digital computer to perform restoration, then the image restoration will be image inpainting. In this paper we use the advantages of Gaussian pyramid & median filter to inpaint large areas. They work together for removal of large object in lesser time.
Keywords: Inpainting, Gaussian pyramid, recursive median, hybrid.

1. Introduction

Gaussian pyramid inpainting is a fast inpainting technique but it can remove only smaller damaged regions. The recursive median inpainting technique can inpaint larger objects with edge preservation. But, this technique slows down as the damaged region becomes larger. Marginal improvements can be obtained by using efficient sorting algorithms. Hence, an hybrid technique by combining these two techniques is proposed in this paper. The performance of recursive median is combined with the speed of Gaussian. Gaussian pyramid reduces the size of damaged region, and the recursive median fills it. The combinations work in unison to inpaint larger object in less time.

Large object removal is one of the interesting applications for commercial use. For example, the complete objects in a scene can be inpainted producing special effect (vanishing of an object), which may have commercial value in blanking the offensive content in an image or streaming video. The infamous ‘airbrushing’ of political enemies is another perfect example of this type [1].

2. Literature Survey

Inpainting technique introduced by Bertalmio, rekindled interest of image processing researchers in the field of inpainting. Over the past decade, many ideas and implementations are proposed to extract the surrounding information to inpaint effectively. There is no unified framework to inpaint structure and texture images. Hence, the previous approaches of inpainting techniques may be broadly classified under two different headings.

- Structure Inpainting
- Texture Inpainting

2.1. Structure Inpainting

Structure inpainting is a pixel based approach, where properties of individual pixels are used to fill-in damaged region. The information derived from surrounding pixels of the damaged region is propagated into it. The structure inpainting techniques may be classified as -

The PDE based techniques treats image as a bound surface created by the pixel locations and partial differential equations are used to model it. The damaged regions are the 'holes' in this image surface. Using some smoothness constraint, damaged region is filled-in by solving the PDEs. Iterative numerical techniques are used to find approximate solution of PDEs with suitable boundary conditions. Some of the PDE based inpainting techniques with their limitations are discussed.

Masnou and J M Morel [2] proposed the inpainting by level lines based on disocclusion. The technique performs inpainting by joining end points of geodesic curves. Bertalmio [3] extended level lines based disocclusion method of Masnou and J M Morel [2]. In [4], the ideas from computational fluid dynamics (CFD) are used to propagate isophote lines. The image intensity is treated as a 'stream function' of a two-dimensional incompressible flowing fluid. The Laplacian of the image intensity plays the role of the vorticity of the fluid and is transported into the region to be inpainted by a vector field defined by the stream function. The technique is designed to continue isophotes while matching gradient vectors at the boundary of the inpainting region. The method is directly based on the Navier-Stokes equations describing fluid dynamics.

Chan and Shen proposed two image inpainting techniques. Total Variation (TV) inpainting model [5, 6] uses the Euler Lagrange modeling. Inside the inpainting domain, this model employs anisotropic diffusion [7] based on contrast of the isophotes. It does not connect broken edges (i.e. single lines embedded in a uniform background). Curvature-Driven Diffusion (CCD) model [8], an extension of TV technique, takes into account the geometric information of isophotes while defining the strength of diffusion process. This allows inpainting over large areas. Although, CCD connects some broken edges but inpainting results in blur. The phase transition in superconductor and Ginzburg-Landau equation [9,10] are used to inpaint the selected areas. In [11] normal and tangential vectors are propagated into damaged/missing regions and image is reconstructed.

A. Telea [12] has proposed a fast marching method (FMM) based on PDE. It is considerably fast and simple to implement than other PDE based techniques without computational overheads. The technique calculates smoothness estimate of image from known neighborhood of the pixel as a weighted average to inpaint. The FMM inpaints the near pixels to the known region first and maintains a narrow band of pixels which separates known pixels from the unknown pixels. The limitation of this technique is in producing blur when the region to be inpainted is thicker than ten pixels.

Bertalmio [13] reformulated the inpainting problem as a particular case of image interpolation in which level lines (isophotes) are propagated. In this technique, a third order PDE is derived based on the local neighborhoods of damaged region and using a Taylor expansion. This PDE is optimal in the sense that it is the most accurate third order PDE which can ensure continuation of level lines into the damaged region. The continuation is strong [14], allowing the restoration of thin structures occluded by a wide gap. It is also contrast invariant.

D. Fisheloy [15] proposed an extension of [4]. The idea is to use fluid equations - the Navier-Stokes equations - as a PDE based method for the image inpainting. The representation of the Navier-Stokes in terms of stream function eases the implementation and the analysis of the inpainting technique.

The Total variation model [5, 6] for image inpainting is an effective method. But the interpolation of this model is limited to creating straight isophotes, not necessarily smoothly continued from the boundary. Peiying Chen [16] made some improvements to propagate the information smoothly from boundary to the damaged region and proposed fourth-order PDE technique to inpaint.

Zhongyu. Xu [17] presents a faster technique based PDEs. This technique is called as quick curvature-driven diffusion's (QCDD) and produces better results with lesser computation time. QCDD model is developed on the basis of the curvature-driven diffusion's (CDD) model. Both, CDD and QCDD models are supported by "connectivity and holistic principle,". These techniques connect a few broken edges, but produce a blurry look after inpainting.

PDE based methods are complex and slow. Also, the edge information is not handled and results show blocky effect for large damaged regions. Sometimes implementation of PDE is numerically unstable.

2.2. Texture Inpainting Techniques

Texture is a group of inter-related pixels, and hence pixel by pixel reconstruction of the structural images cannot be used directly to inpaint the textured images. The texture inpainting is pasting the texture into the damaged region. Texture to be pasted can be obtained either by synthesizing it or searching for a similar patch in the image (exemplar based). Texture inpainting technique fills-in the damaged region with synthesized texture patch or by searched patch.

Criminisi [18] developed an efficient and simple approach to encourage fill-in from the boundary of the missing region where the strength of nearby isophote was strong, and then used the sum of squared difference (SSD) to select a best matching patch among the candidate source patches. In the technique of Criminisi the region filling is determined by the priority based mechanism. Cheng [19] generalized the priority function for the technique given in [20] to provide a more robust performance. Komodakis [20] defined a global objective function to inpaint. This method is computationally expensive. Wong [21] developed a weighted similarity function to inpaint texture. The similarity function uses several source patches to reconstruct the target patch instead of using a single source patch. Fang [22] developed a rapid image inpainting technique which consists of a multiresolution training process and a patch-based image synthesis process. Xu [23] proposed two novel concepts of sparsity at the patch level for modeling the patch priority and patch representation. Exemplar based approaches achieve better inpainting compared to the diffusion-based ones but adopt complex strategies. These techniques mainly deals with texture synthesis and do not account structured background.

3. Inpainting using Multiresolution Gaussian Pyramid

Consider an image $f_{l+1}(u,v)$, ($1 \le u \le M$,$1 \le v \le N$) at resolution 2^{l+1} ,$-L \le l \le -1$. The image $f_l(u,v)$ at resolution 2^l which is reduced by half in both resolution and sample density is given by

$$f_l(u,v) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} f_{l+1}(2u+m, 2v+n)w(m,n) \qquad \text{(Reduce)} \qquad (1)$$

And the expanded version of an image $f_l(u,v)$ at resolution 2^l i.e. the image $f_{l+1}(u,v)$ at resolution 2^{l+1} is given by

$$f_{l+1}(u,v) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} f_l\left(\frac{u-m}{2}, \frac{v-n}{2}\right)w(m,n) \qquad \text{(Expand)} \qquad (2)$$

where $w(m,n)$ is Gaussian filter of size 5×5 and is used to generate Gaussian pyramid. This window is called as Gaussian generating kernel [26]. The window $w(m,n)$ is separable i.e. $w(m,n) = w(m)w(n)$, where $w(\cdot)$ is a normalized one dimension Gaussian filter of length 5 and is given by

$$\sum_{m=-2}^{2} w(m) = 1 \qquad (3)$$

And it is symmetric: $w(-i) = w(i)$ for i = 0, 1, 2 and having equal contribution.

In this technique, a Gaussian pyramid [24] of resolutions 2^{-1} to 2^{-L}, of an input image is generated. The input image f_0 is downsampled using Gaussian pyramid up to L resolution levels to obtain images f_{-1}, f_{-2},

…………, f_{-L} at resolution levels 2^{-1} to 2^{-L}, respectively. The damaged region Ω_0 progressively reduces to $\Omega_l = \Omega_0 2^l$, $-L \le l \le -1$. After 2^{-L} resolution levels the expand operation is applied. The image f_{-L} corresponding to lowest resolution is expanded to obtain f'_{-L+1}. The damaged region, Ω_{-L+1} of image f_{-L+1} is considered and the pixels of this region are substituted by the pixels of corresponding region from f'_{-L+1}. This substitution of Gaussian interpolated pixels assumes the processes of diffusion at that resolution. The expand operation followed by substitution is repeated for subsequent resolution levels up to original resolution to obtain inpainted image.

4. Recursive Median Inpainting

The inpainting using recursive median filter is introduced with respect to the Bertalmio's inpainting technique [3]. The iterative inpainting technique of Bertalmio's is based on Laplacian diffusion. The recursive median inpainting is a non-iterative and it assumes Laplacian distribution of pixels to find the best pixels to fill-in the damaged region.

Consider an image $f(u,v)$ of size $M \times N$ with Ω as damaged region. The Laplacian at a pixel (u,v) is defined as

$$L\,(u,v) = f_{xx}(u,v) + f_{yy}(u,v) \tag{4}$$

The pixels value at t^{th} instant (t^{th} iteration) is given by

$$f^{t}(u,v) = f^{t-1}(u,v) + \mu \begin{bmatrix} L^{t-1}(u+1,v) - L^{t-1}(u-1,v) \\ L^{t-1}(u,v+1) - L^{t-1}(u,v-1) \end{bmatrix}^T \begin{bmatrix} \dfrac{-\left(f_x^{t-1}(u,v)\right)}{\sqrt{\left(f_x^{t-1}(u,v)\right)^2 + \left(f_y^{t-1}(u,v)\right)^2}} \\ \dfrac{\left(f_y^{t-1}(u,v)\right)}{\sqrt{\left(f_x^{t-1}(u,v)\right)^2 + \left(f_y^{t-1}(u,v)\right)^2}} \end{bmatrix} \forall (u,j) \in \Omega \tag{5}$$

where $f_x(u,v)$, $f_x(u,v)$, and $f_{xx}(u,v)$ & $f_{yy}(u,v)$ are first and second order derivatives of an image $f(\cdot)$ at (u,v) respectively and μ is diffusion constant (<1). We observe that, the rate of change of $f(\cdot)$ at (u,v) is proportional to the difference between the average value of $f(\cdot)$ around (u,v) and the value of $f(\cdot)$ at (u,v) i.e. update at a pixel (u,v) is based on four-neighborhood. The process of diffusion is linear and is based on deterministic model. Large number of iterations is required to reach steady state. In view of this, a nonlinear probabilistic model based recursive median filter is proposed.

In recursive median filter, the pixel is estimated from a larger neighborhood based on a nonlinear higher order statistics. The pixel obtained by recursive median filtering is the maximum likelihood estimate (MLE) of location for the Laplacian distribution. In the present context, the pixel estimate in some sense is diffusion at steady state. Therefore, instead of Laplacian diffusion, we use recursive median filter to inpaint. Hence, the recursive median inpainting is given by the equation-

$$y\,(u,v) = RM2D\left(f(u,v)\right) \qquad \text{for } \forall (u,v) \in \Omega \tag{6}$$

Wher RM2D is the two dimension recursive median filter.

5. Hybrid Approach for Inpainting Large Object

The inpainting techniques as applied to object removal yield satisfactory results for small sized objects but fail for bigger sized objects. Recursive median inpainting for large damaged regions is slower. Hence, we propose hybrid approach, which exploits the best feature of recursive median within the framework of multiresolution Gaussian.

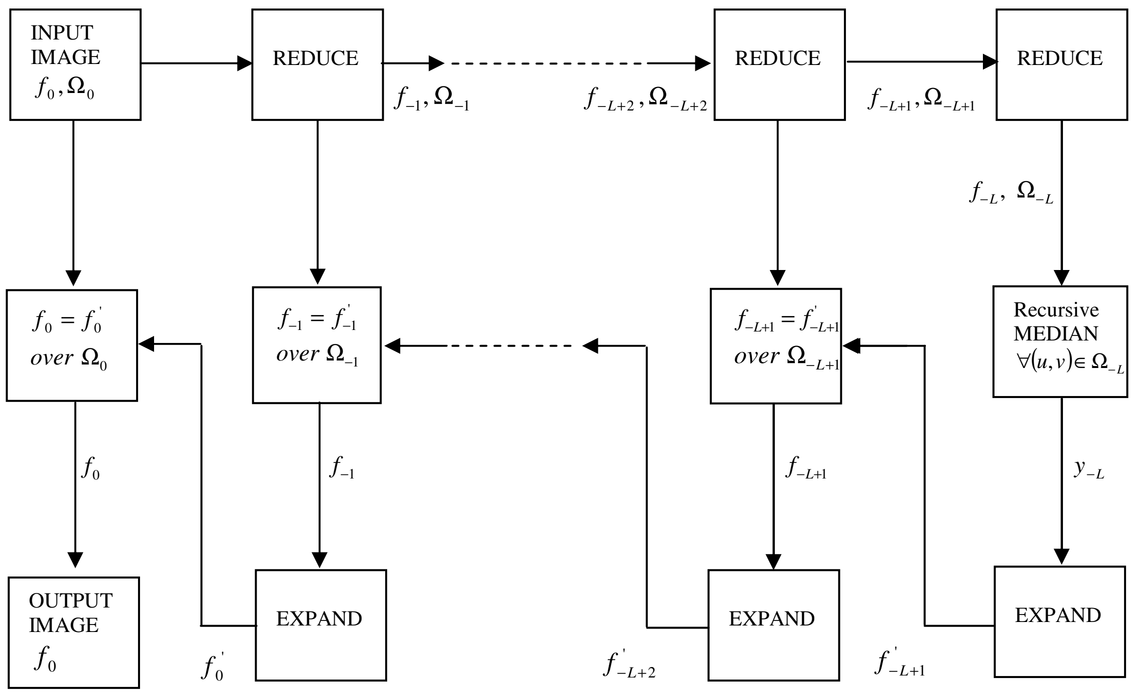

Figure 1 Block diagram of proposed hybrid approach. RM2D is applied only once at the lowest resolution.

The main idea in this technique is to down sample the input image using Gaussian pyramid and reduce the size of the object to be removed. At the lowest resolution, recursive median values of pixels are diffused into object region from its exterior. We substitute the object region of an image in the second lowest resolution by expanding diffused image at the lowest resolution level. The process of expansion and substitution, similar to Gaussian pyramid technique is carried out till the zeroth i.e. original resolution to obtain output image with the object removed. The down sampling reduces the size of an object to be removed and hence recursive median filter removes the object in lesser time. Expansion (upsampling) and substitution constructs the homogeneous background in place of the object. This technique produces better results for the removal of medium and large size objects.

In the proposed technique, the object to be removed i.e. target region is replaced with the homogeneous background. As input image f_0 is downsampled and low pass filtered to obtain images f_{-1}, f_{-2}, f_{-3},……, f_{-L} at resolutions 2^{-1} to 2^{-L}, respectively, the size of target region, Ω_0 reduces to $\Omega_{-L} = \Omega_0 \times 2^{-L}$. Recursive median values of the pixels are used to fill-in the target region Ω_{-L} to obtain y_{-L}. The diffused image y_{-L} is upsampled to obtain f_{-L+1}'. The pixels in target region Ω_{-L+1} of an image f_{-L+1} are substituted by corresponding pixels from f_{-L+1}'. Then resulting image f_{-L+1} is again expanded to obtain f_{-L+2}' and substituted by object region Ω_{-L+2} of an image f_{-L+2}. The process of expansion and substitution is carried out till zeroth i.e. original resolution to obtain output image with the object removed. The block diagram of this technique is as shown in Figure 1.

Algorithm:

The algorithm constitutes of three operations- (i) Reduce operation (ii) Recursive median inpainting and (iii) Expand and Substitution operation.

$f_0(u,v)$: Input image with Ω_0 as the object region to be filled.

$f_l(u,v)$: Image at resolution 2^l with object region $\Omega_l = \Omega_0 \times 2^l$.

The Algorithm

Begin

Reduce operation

for $(l = -1 : -1 : -L)$

$$f_l(u,v) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} f_{l+1}(2u+m, 2v+n)w(m,n)$$

Store $[f_l(u,v), \Omega_l]$

endfor

$f_{-L}(u,v)$ is the output image of the *Reduce operation* at lowest resolution 2^{-L} with object region Ω_{-L}, where $1 \le u \le M/2^L$ and $1 \le v \le N/2^L$.

Recursive median inpainting

$$y_{-L}(u,v) = RM2D(f_{-L}(u,v)) \text{ for } \forall(u,v) \in \Omega_{-L}$$

$$f_{-L}(u,v) = y_{-L}(u,v)$$

Expand operation

for $(l = -L : -1 : -1)$

$$f'_{l+1}(u,v) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} f_l\left(\frac{u-m}{2}, \frac{v-n}{2}\right)w(m,n)$$

Substitute operation

$$f_{l+1}(u,v) = f'_{l+1}(u,v) \quad \text{for } \forall(u,v) \in \Omega_{l+1}$$

endfor

End

The algorithm replaces the original input image by the output image with homogeneous background in place of the object removed.

6. Results and Applications

To calculate PSNR, artificially we paste some objects or subimages on the original images to create a new image. These artificially placed objects are removed and homogeneous background is created. The results of the proposed algorithm are compared with Bertalmio, FoE and Gaussian pyramid techniques. The implementations of the respective authors are used to obtain the results of an object removal. We argue again that the PSNR measure, if it is in tandem with the qualitative assessments, then the proposed algorithm can be extended to all the practical applications of an object removal. Hence, we perform two different sets of experiments-

IJCSC 0973-7391 Volume 7 • Number 1 Sept 2015 - March 2016 pp.117-128 available online at www.csjournalss.com

- In the first set of experiments we paste an object on image and the pasted object is removed. The PSNR can be calculated for these images and compared with qualitative assessment.
- In the second set of experiments, the existing object from an image is removed, where PSNR cannot be calculated and can be viewed as application of inpainting.

Set I:

Initially, the proposed hybrid technique is tested on - fish image (Figure 2a) and synthetic plain image (Figure 3a). On these images artificially we paste a fish and combination of Lena's face, Cameraman's face and Abraham Lincoln's face as shown in the Figures (2b & 3b) respectively. These objects are removed using Bertalmio's inpainting technique (Figures 2c & 3c), FoE inpainting technique (Figures 2d & 3d) with 2000 iterations, Gaussian pyramid inpainting technique (Figures 2e & 3e) and proposed hybrid approach inpainting technique (Figures 2f & 3f). Later, to test the efficacy of the proposed inpainting technique, the natural images (Figures 4a & 5a) are used. These images are pasted with objects like child face, and Lena's face on original image to obtain synthetic images (Figures 4b & 5b). These pasted objects are removed using Bertalmio's inpainting technique (Figures 4c & 5c), FoE inpainting technique (Figures 4d & 5d) with 2000 iterations, Gaussian pyramid inpainting technique (Figures 4e & 5e) and proposed hybrid approach inpainting technique (Figure 4f & 5f).

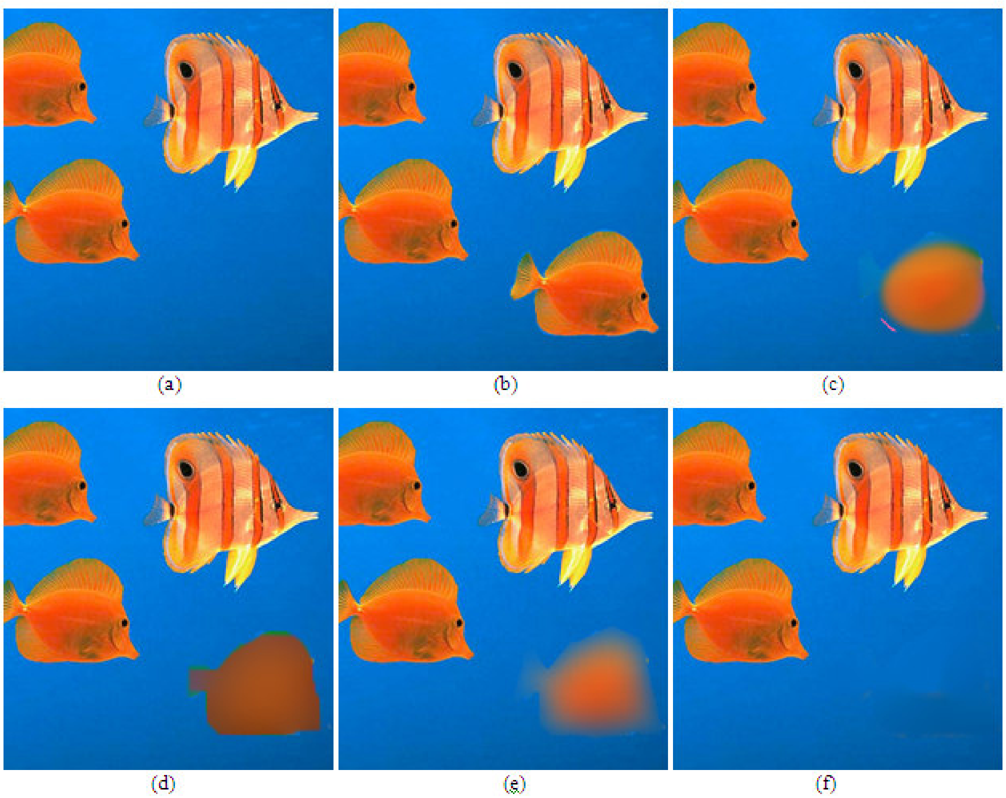

Figure 2 Inpainting a fish placed at the right bottom of fish image. (a): Clean undamaged fish image with three fishes. (b): An additional fish as an object is placed at the right bottom of clean image. (c): Bertalmio's technique with PSNR=20.7746 dB. (d): FoE technique with PSNR=20.6190 dB. (e): Gaussian pyramid technique with PSNR= 22.2367 dB. (f): Hybrid approach with PSNR=47.4857 dB.

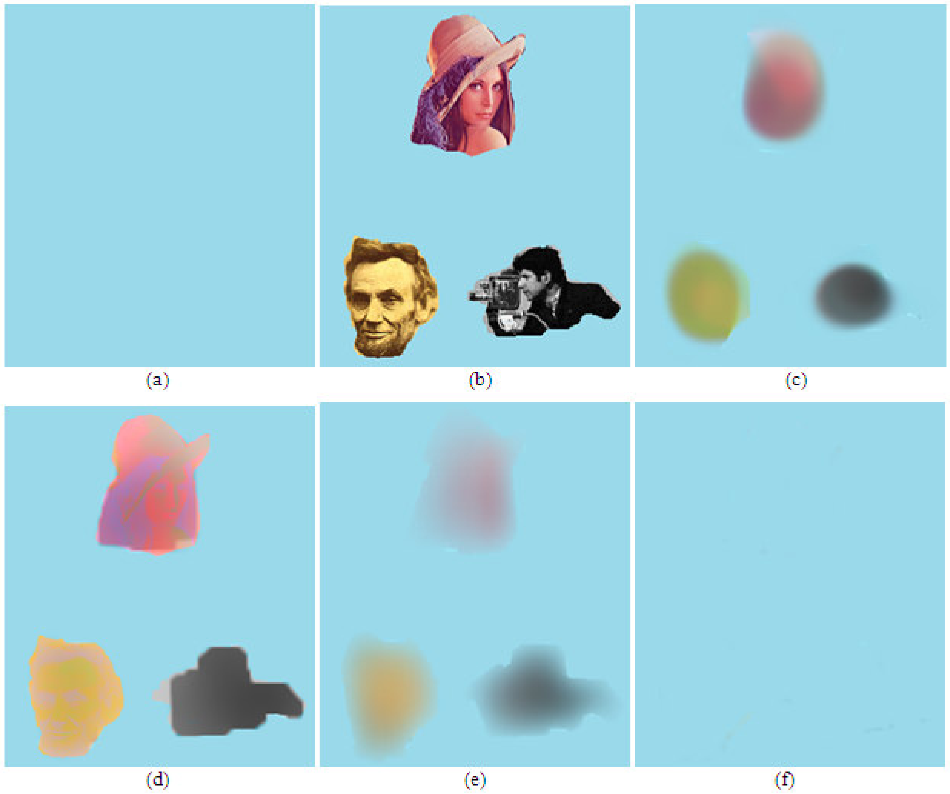

Figure 3: Inpainting the faces of Lena's, Abraham's and Cameraman's placed on plain background. (a): Clean undamaged plain image. (b): Lena's, Abraham's and Cameraman's faces are placed on plain image. (c): Bertalmio's technique (PSNR=19.1492 dB). (d): FoE technique with PSNR=16.0342 dB. (e): Gaussian pyramid technique with PSNR= 22.1371 dB. (f): Proposed hybrid approach with PSNR=54.8703 dB.

Figure 4 Inpainting the child's face placed artificially on the left side of child's image 1. (a): Clean undamaged child's image. (b): Subimage is placed on clean image. (c): Bertalmio's technique with PSNR=26.4312 dB. (d): FoE technique with PSNR=25.6414 dB. (e): Gaussian pyramid technique with PSNR=28.6463 dB. (f): Proposed hybrid approach with PSNR=45.6046 dB.

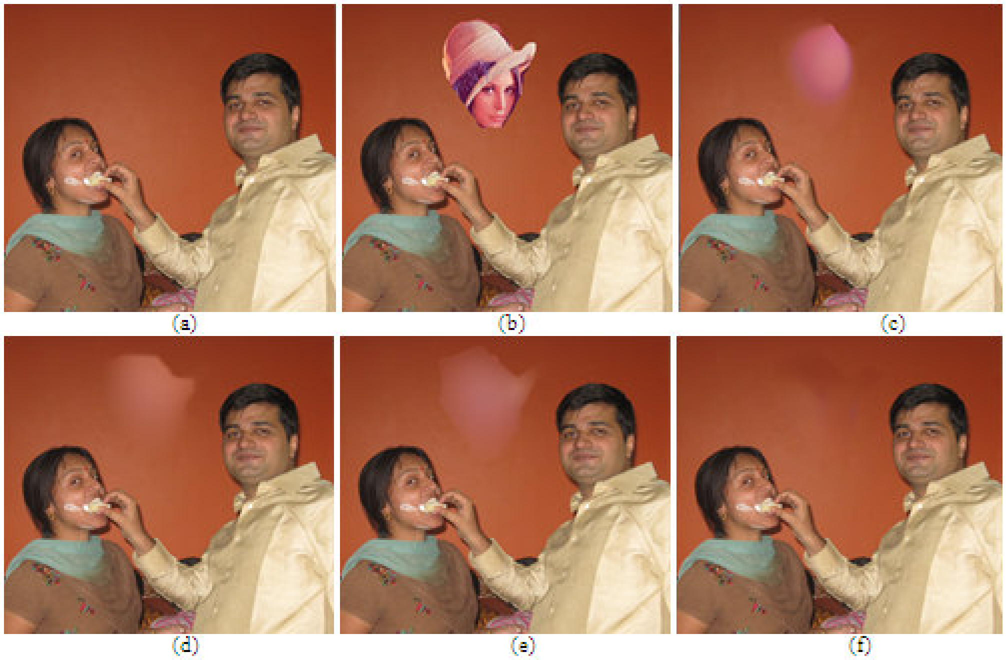

Figure 5 Inpainting Lena's face placed on pair image. (a): Clean undamaged pair image. (b): A sub image (Lena) is placed on clean image. (c): Bertalmio's technique (PSNR=25.7076 dB). (d): FoE technique (PSNR=31.9746 dB). (e): Gaussian pyramid technique (PSNR= 31.63 dB). (f): Proposed hybrid approach with PSNR=44.5434 dB.

The PSNR measure is well suited for the testing purpose, as we paste objects on original image and then object is removed to calculate PSNR between original and result. In general, such a measure is not feasible as there is no original image. Hence, we have to rely on qualitative evaluation only. We observe that the PSNR measure (Table 5.1) and qualitative assessments give identical interpretations. Therefore, we envisage the proposed hybrid approach to perform similarly to every other image and hence it is extended to object/s removal application expecting similar performance.

Figure No	***Image Name***	***PSNR (dB)***			
		Bertalmio's Inpainting	***FoE Inpainting***	***Gaussian Pyramid Inpainting***	***Proposed Hybrid Approach***
2	Fish	20.7746	20.619	22.2367	47.4857
3	Synthetic Plain	19.1492	16.0342	22.1371	54.8703
4	Child	26.4312	25.6414	28.6463	45.6046
5	Pair	25.7076	31.9746	31.63	44.5434

Table 1 PSNR comparisons of our proposed hybrid technique with Bertalmio's, FoE and Gaussian pyramid techniques. Both Bertalmio's and FoE results are obtained after 2500 iterations.

Set II:

The proposed hybrid approach is tested to remove the bigger object/s like bird, computer, and coins from the image as shown in the Figure (5.8a to 5.13a), respectively. The results of the proposed hybrid approach are as shown in the Figures (5.8f to 5.13f) and compared with the results of Bertalmio's shown in the Figures (5.8b to 5.13b), FoE shown in the Figures (5.8c to 5.13c), Gaussian pyramid shown in the Figures (5.8d to 5.13d) and recursive median technique shown in the Figures (5.8e to 5.13e). The visual quality of results of recursive median and hybrid approach is as expected. But Bertalmio's, FoE and Gaussian pyramid techniques fail to remove the bigger object/s and produce artifacts in place of it.

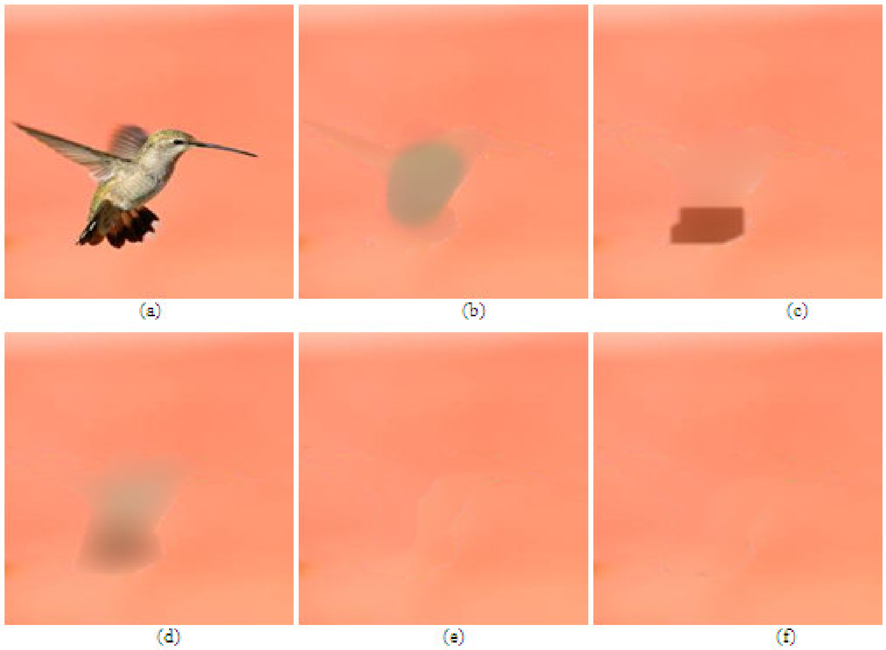

Figure 6 Removal of bird from bird's image. (a): Original image with big bird. (b): Bertalmio's technique. (c): FoE technique. (d): Gaussian pyramid technique. (e): RM technique. (f): Hybrid approach.

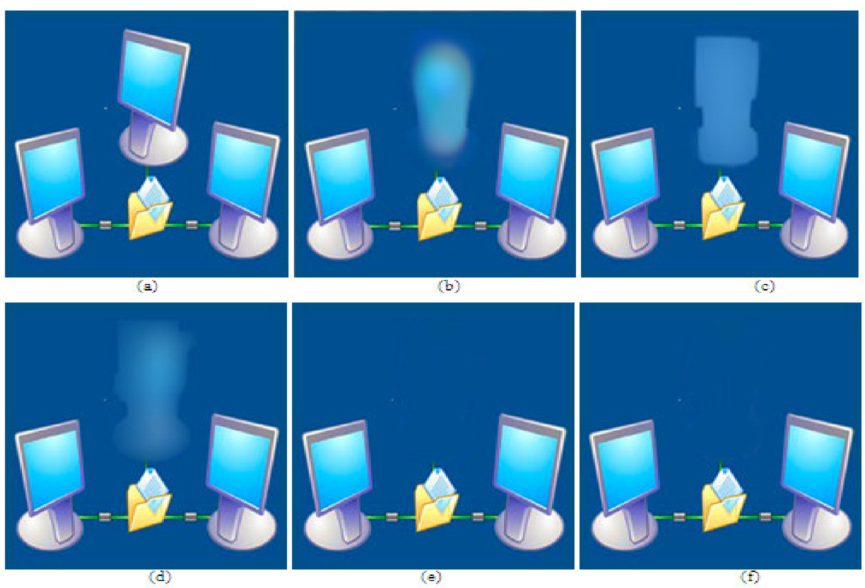

Figure 7 Removal of a center computer from LAN image. (a): Original LAN image with three computers. (b): Bertalmio's technique. (c): FoE technique. (d): Gaussian pyramid technique. (e): RM technique. (f): Proposed hybrid approach.

IJCSC 0973-7391 Volume 7 • Number 1 Sept 2015 - March 2016 pp.117-128 available online at www.csjournalss.com

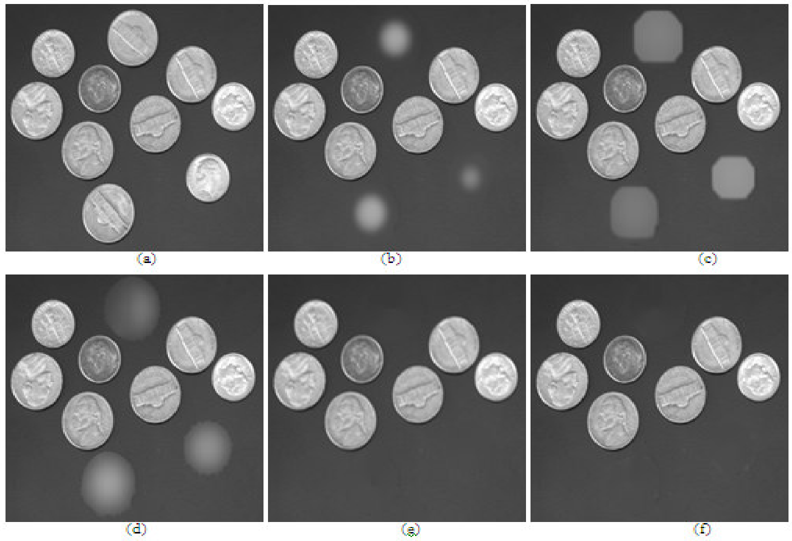

Figure 8 Removal of three coins from coins image. (a): Original multiple coin image. (b): Bertalmio's technique. (c): FoE technique. (d): Gaussian pyramid technique. (e): RM technique. (f): Hybrid approach.

7. Comparison of Proposed Hybrid Inpainting Approach with Others & Conclusion

The execution time and PSNR of some of the results of all the proposed structure inpainting techniques are tabulated in the Table 2. It can be observed that Gaussian pyramid is a fast technique. The Gaussian pyramid and recursive medium filter work are nearly the same for small damaged region but for larger damaged region recursive median inpainting performs better. At still larger regions Gaussian pyramid fails to inpaint. In addition to this, recursive median inpainting can inpaint with both homogeneous as well as heterogeneous backgrounds, whereas Gaussian pyramid technique can be used only for homogeneous background. The disadvantage of recursive median inpainting is, it is expensive in terms of time. A tradeoff between time and quality of inpainting is to use Gaussian pyramid and recursive median filter together-Hybrid approach. As envisaged, hybrid approach is fast and better for larger regions. But, it restricts inpainting to homogeneous regions with superior results than recursive median.

Figure No	*Image Name*	*Execution Time (Sec)*			*PSNR (dB)*		
		Gaussian Pyramid Inpainting	*Recursive Median Inpainting*	*Proposed Hybrid Approach*	*Gaussian Pyramid Inpainting*	*Recursive Median Inpainting*	*Proposed Hybrid Approach*
SET 1							
2	Fish	4.3948	2235.7442	30.9229	22.2367	46.9557	47.4857
3	Synthetic	4.4218	1676.1934	78.7008	22.1371	48.7902	54.8703
4	Child	3.8215	2077.9752	31.3579	31.554	47.7478	45.6064
5	Pair	4.3167	1917.3481	27.7367	31.63	45.0018	44.5434
SET 2							
6	Bird	2.6459	2785.1857	90.3100	No Clean Images		
7	LAN	5.9001	1681.5055	150.6307			
8	Coins	3.8786	2356.7585	110.3586			

Table 2 Execution time and PSNR comparisions of hybrid approach with other structure inpainting techniques on MATLAB 2007b using Intel i3, 2.53 GHz processor.

REFERENCES

[1] D. King. *The commissar Vanishes.* Henry Holt and Company, 1997.

[2] S. Masnou and J.M. Morel. *Level Lines Based Disocclusion*. 5th IEEE International Conference on Image Processing (ICIP), Chicago, IL. Oct4-7, vol.3, 1998, pp 259-263.

[3] M. Bertalmio, G. Sapiro, V. Caselles, and C. Ballester. *Image Inpainting.* Proceedings of SIGGRAPH. Computer Graphics Processing, 2000, pp 417-424.

[4] M. Bertalmio, A. L. Bertozzi and G. Sapiro. *Navier-Stokes, Fluid Dynamics and Image and Video Inpainting*. IEEE International Conference on Computer Vision and Patter Recognition (CVPR), vol.1, 2001, pp 355-362.

[5] F. Chan and J. Shen. *Mathematical Models for Local Deterministic Inpainting*. UCLA Computational and Applied Mathematics Reports 00-11, March 2000, pp 00-11.

[6] H. Grossauer. *Digital Inpainting using the Complex Ginzburg-Landau Equation*. Scale Space Method in Computer Vision, Lecturer Notes 2695, 2003.

[7] P. Perona and J. Malik. *Scale-Space Edge Detection Using Anisotropic Diffusion*. IEEE transaction on Pattern Analysis and Machine Intelligence (PAMI), vol.12, No. 7, July 1990.

[8] F.Chan, S.H. Kang and J. Shen. *Euler's Elastica and Curvature-Driven Diffusion*. SIAM Journal, Applied Mathematics, vol.63, No.2, 2002, pp 564-592.

[9] H. Grossauer. *Digital Inpainting using the Complex Ginzburg-Landau Equation*. Scale Space Method in Computer Vision, Lecturer Notes 2695, 2003.

[10] H. Grossauer and O.Scherzer. *Using complex Ginzburg-Landau Equation for Image Inpainting.* Scale Space Method in Computer Vision, Lecturer Notes 2696, 2003.

[11] X. C. Tai, S. Osher and R. Holm. *Image Inpainting using a TV-Stokes Equation*. In, Image processing Based on PDE, Springer, Heidelberg, 2006, pp 473-482.

[12] A. Telea. *An Image Inpainting Technique Based on the Fast Marching Method*. Journal of Graphics Tools, vol.9, No.1, ACM press, 2004, pp 25-36.

[13] M. Bertalmio. *Contrast Invariant Inpainting with a Third Order, Optimal PDE*. IEEE International Conference on Image Processing (ICIP 2005), Sep 2005. pp 778-781.

[14] M. Bertalmio. *Strong Continuation*, *Contrast Invariant Inpainting with a Third Order, Optimal PDE*. IEEE Transaction on Image Processing, vol.15, No.7, July 2006, pp 1934-1938.

[15] D. Fishelov and Nir Sochen. *Image Inpainting via Fluid Equation*. International Conference on Information Technology: Research and Education (ITRE 06), Oct 2006, pp23-25.

[16] Peiying Chen and Yuandi Wang. Fourth-Order Partial Differential Equations for Image Inpainting. International Conference on Audio, Language and Image Processing (ICALIP 2008), July 2008. pp 1713-1717.

[17] Zhongyu.Xu. *Image Inpainting Algorithm Based on Partial Differential Equation*. International Colloquium on Computing, Communication, Control, and Management- ICCCM '08, 2008, pp 120-124.

[18] A. Criminisi, P.Perez and K. Toyama. *Object Removal by Exempler-Based Inpainting*. IEEE Transaction on Image Processing, vol. 13, No 9, September 2004, pp 1200-1212.

[19] WH Cheng, CW Hsieh, Sh. K. Lin, Ch .W. Wang, and JL Wu. *Robust Algorithm for Exemplar Based Image Inpainting.* IEEE Transaction on Image Processing, 2005.

[20] N. Komodakis and G. Tziritas. *Image Completion using Efficient Belief Propagation via Priority Scheduling and Dynamic Pruning.* IEEE Transactions on Image Processing, vol. 16, 2007, pp. 2649 -2661.

[21] A. Wong and J. Orchard. *A Nonlocal Means Approach to Exemplar based Inpainting*. Proceedings of the 15th IEEE International Conference on Image Processing, 2008, pp. 2600-2603.

[22] C. Fang and J. J. Lien. *Rapid Image Completion System using Multiresolution Patch based Directional and Non-directional Approaches*. IEEE Transactions on Image Processing, vol. 18, 2009, pp. 2769-2779.

[23] Z. Xu and S. Jian. *Image Inpainting by Patch Propagation using Patch Sparsity.* IEEE Transactions on Image Processing, Vol. 19, 2010, pp. 1153-1165.

[24] Burt and Adelson. *The Laplacian Pyramid as a Compact Image Code*. IEEE Transaction on communication, vol.COM, No 4, April 1983, pp.532-540.