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HIERARCHICAL SINGLE IMAGE SUPER RESOLUTION INPAINTING

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ABSTRACT

The main goal of any digital image inpainting algorithm is to reconstruct the missing or damaged regions in a visually plausible way. Inpainting techniques covers widespread use in applications that include various applications instead of error recovery, red-eye removal, multimedia editing. Digital image inpainting refers to a method used for filling in the lost or spoiled regions of an image using information from the nearby area. A novel structure meant for examplar-based inpainting performing first the inpainting on a coarse version of the input image then hierarchical super-resolution algorithm is then used to recover details on the missing areas. The benefits of presented approach is that it is easier to inpaint low-resolution pictures than high resolution ones. This approach the low-resolution input picture is inpainted several times with different configurations, to obtain required quality results. Obtained results are pro-fessionally combined with loopy belief propagation and details are recovered by a single image super-resolution algorithm. Experimental results in a perspective of image editing and texture synthesis demonstrate the efficiency of the proposed technique as best candidate for high resolution images.

KEY WORDS—single image super resolution Inpainting, Exam-plar based inpainting, Object removal

I. INTRODUCTION

In the field of image processing filling the absent Areas (holes) from the image is a problem in many image processing applications [1]. Image inpainting is the procedure of recon-structing lost or deteriorated parts of images. Existing methods are broadly classified into two sections first Diffusion based approach and second Examplar based approach. These two existing methods are inspired from the texture synthesis tech-niques [2]. Dispersal based approach generates the isophotes via diffusion based on variation in structure or variation in methods [3], the main drawback of diffusion based approach is have a tendency to introduce some blur when the filling the missing area is very large. Latter method of approach is Examplar based approach which is quite straightforward and innovative, in this method copy the best sample from known image neighborhood. Initially Examplar method approach is implemented on object removal as chronicled in [4], searching the alike patches is done by using the priori rough estimate method of the inpainted image values utilizing the multi-scale approach.

Two varieties of methods (diffusion based approach and Examplar based approach) are then pooled, for case in point by utilizing the organization tensor to compute the priority of the patches to be crammed in [5]. Latter the examplar approach joint with the super resolution (SR) algorithm. It's a two steps approach, firstly rough (coarse) version of the input image is inpainted then in second step originating the high clarity image from the inpainted image. Even though lot of improvement completed in the past decade on examplar based inpainting at rest lot problems to be addressed in all the main area of concern is patch size and filling the holes related to settings configuration. This problem is here addressed by several input inpainting versions to yield the concluding inpainting picture behind combining the all input inpainting versions. Make a note of that Inpainting is applied on the irregular (coarse) version of the input image when the filling area (hole) is very large which reduces the impact of computational complexity and robust behavior against noise entities. In this type of scenario concluding complete resolution picture is retrieved from the marvelous resolution algorithm.

This paper is organized as follows. In Section II short review of the proposed hirachical super resolution based inpainting algorithm is presented. In Section III, covers details of the inpainting algorithm. Section IV presents the super-resolution method. Experimental result and comparison of obtained re-sults with up to date algorithms are performed in Section V. finally we conclude about this work on the basis of obtained results.

II. LITERATURE SURVEY

Kokaram et al. [4] use movement estimation and autoregressive models to exclaim losses in films from adjacent frames. The fundamental idea is to copy into the breach the right pixels from neighboring frames. The system cannot be applied to still images or to films where the regions to be inpainted span many frames. Hirani and Totsuka [5] unite frequency and spatial domain information in turn to fill up a specified region with a selected texture. This is a very easy technique that produces unbelievable high-quality results. Alternatively, the algorithm mostly deals with texture synthesis and not with prearranged background and requires the user to select the texture to be copied into the region to be inpainted. For images anywhere the region is to be replaced covers more than a few different structures, the user would require to go through the great work of segmenting them and searching through the corresponding replacements throughout the picture. Though a part of this search can be finished without human intervention, this is extremely time consuming and requires the non-trivial selec-tion of many critical parameters [6]. Other texture synthesis algorithms are presented in [6, 7], can be used as well to restructure a pre-selected texture to fill-in a square region to be inpainted.

D. Cho et. al [29] proposed method which perform very well when the region to be reconstructed is very small, but fails in proper reconstruction as the area increases. Considering this problem Hierarchical method by which the area to be inpainted is reduced in multiple levels and Total Variation (TV) method is used to inpaint in each level. This method tries to utilize the advantage of the TV method while keeping the mask size less than a predefined value all the time. Though this method produces the gray levels better than other methods it results in some amount of blurring as the number of levels increases. Nazarlu et. al [32] used two approaches segmentation and inpainting. Segmentation approach used to separate damaged area and inpainting is performed to recover image. Segmentation module is selected by considering the inpainting effects. The valuation of segmentation result guides system to construct Heuristic rules.

Babu et. al [23] experienced a problem that hole caused by dis-occlusion in depth image have a bad effect on stereoscopic image quality. To solve the problem hole filling method using image segmentation-based image inpainting is introduced. In this method hole filling not only gives high quality result but also possibility of general purpose method as real-time appli-cation and generate natural stereoscopic image using DIBR. Vemulapally et. al [28] introduced a method for examplar-based inpainting. To inpaint on a rough version of the input image, a hierarchical super-resolution algorithm is used to recover the missing areas. The advantage of this approach is that it is easier to inpaint low-resolution pictures than high-resolution ones. The gain is both in terms of computational complexity and visual quality. A data term is used to improve the patch propagation. They introduced a new coefficient for propagating structure components accurately. With help of this method video can also be inpainted. The damaged video can be inpainted frame by frame.

B.Wang et. al [30]. introduced an algorithm for image inpainting that attempts to replicate the basic techniques used by professional restorators. The basic idea is to smoothly prop-agate information from the surrounding areas in the isophotes direction. The user needs only to provide the region to be in-painted; the rest is automatically performed by the algorithm. The in-painted images are sharp and without color artifacts. The in painted of a blur version of the input image permits to decrease the computational complexity, to be low sensitive to sound and to operate with the image structures dominant orientations. This technique reducing the total restoration time. Chatur et. al [31]introduced a new angle of looking towards image inpainting techniques said that applications of inpainting techniques not limited to error recovery, red-eye removal, multimedia editing. He discusses inpainting techniques in the context of digital artwork restoration. He proposed a simple and fast inpainting algorithm based on an examplar based method for scratch or text removal, object removal and missing block completion and proposed a method for completion of holes in images and videos. Successfully removed the fore-ground object and completed the background. His framework is appropriate for video completion. This application is indeed very time-consuming. The use of the proposed framework could dramatically reduce the computational time.

III. TECHNIQUES FOR IMAGE INPAINTING

The challenging here is the image completion of large missing regions. In this paper, inpainting method is introduced using a examplar based method and single-image super resolution(SR) algorithm. Figure 1: illustrates the main concept of proposed method. The following steps are performed:

step 1: A low-resolution image is first built from the original picture.

step 2:An inpainting algorithm is applied to fill-in the missing pixels in the image.

step 3:The quality of the inpainted regions is improved by using a single-image super resolution (SR) method. In this approach, Inpainting is based on examplar technique and super-resolution algorithm of low resolution images are de-scribed in the below sections. Operation: There are two main and sequential operations are used in the composition of proposed methods. The first one is nonparametric patch sampling method used to fill-in missing regions rather than filling in missing regions at the original resolution, the inpainting algorithm is applied on a coarse version of the input image. There are several reasons for performing the inpainting on a low-resolution image. First, the coarse version of input image is compared with the gist [15] that represents some important structures of the image. Performing inpainting on coarse version of the image is much easier since the inpainting would be less contingent on local orientation or even noise. Second as the picture to inpaint is smaller than the original one, the computational time to inpaint is significantly reduced when compared to inpaint a full resolution image. The output of the first operation is used as input to the next operation that is the second operation. Its goal is to improve the quality of the image using a single image SR approach a low-resolution input image depends on the first step of the inpainting process this obtains a high-resolution using a set training examples, which are taken from the known part of the input picture. In figure 1, the new method it represents is generic since there is no constraints on both the number and type of inpainting methods used in the first pass, one could imagine using different settings or methods to fill-in the low resolution images and to fuse results that would increase the robustness and visualization of inpainting obtained by the combination of three methods.

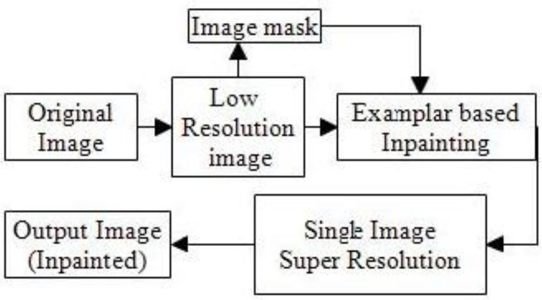

Figure 1: Block Diagram of Image Inpainting.

IV. PROPOSED METHODOLOGY

In this section brief overview of proposed method is given, it contains information about block of proposed algorithm and step by step action of overall implementation process, with input images and their specification. Steps of implementation for proposed system

Step 1: Read the original image in RGB format.

Step 2: Read the mask image in binary format. Step 3: Inpainting algorithm is applied.

Step 4: Patch priority based on sparcity based priority approach to select which patch has to be selected

Step 5: Apply inpainting for different M levels using different parameter setting.

Step 6: To combine different inpainted versions using loopy belief propagation.

Step 7: Inpainted image is obtain.

Step 8: Super resolution(SR) algorithm is applied.

Step 9: Dictionary building prepares pair of corresponding low resolution (LR) and high resolution (HR) image pair.

Step 10: Filling order by sparcity passed logic.

Step 11: A poisson and alpha blending is applied to hide seams between known and unknown part.

Step 12: Final inpainted image is obtain.

In above given steps after applying mask on image we have used Examplar Based Inpainting of low resolution Images, The Examplar-based inpainting method is used to fill in the low-resolution images. In the two methods, the first one is based on a non-parametric patch sampling where as the second one is based on partial derivatives equation [2]. Here examplar based method follows the two classical steps: the filling order computation and the texture synthesis. These are described in the below sections.

1) Patch priority and filling order: The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures where a high priority indicates the presence of structure. The priority of a patch centered on p is just given by a data term. Three different data terms have been tested: gradient-based priority [4], tensor-based [9] and sparsity-based [15]. In a search window, a template matching is performed between the current patch and neighboring patches that belong to the known part of the image. By using a non-local means approach, a similarity weight is computed for each pair of patches. The sparsity-based priority is more robust and visually improves the final result compared to the gradient and tensor-based priority. In the following, this method is used to compute the filling order.

2) Texture synthesis: The filling process starts with the patch having highest priority. The candidates used to fill in the known part of the current patch are com-posed of the K most similar patches located in a local neighborhood cantered on the current patch. They are combined by using a nonlocal means approach. A major problem of local neighbour search is its tendency to get stuck at a particular place in the sample image and to produce verbatim copying. This kind of regions is often called garbage region. This problem can be overcome this issue, we combine inpainted pictures obtained when different settings are used. In this study, we consider M = 13, meaning that the low-resolution picture is inpainted 13 times. Parameters are given in Table I: the patch size is chosen between 5 x 5, 7 x 7, 9 x 9 and 11 x 11. The lling order is computed by either the sparsity-based or the tensor-based method. The input picture can also be rotated by 180 degrees. This allows changing the lling order.

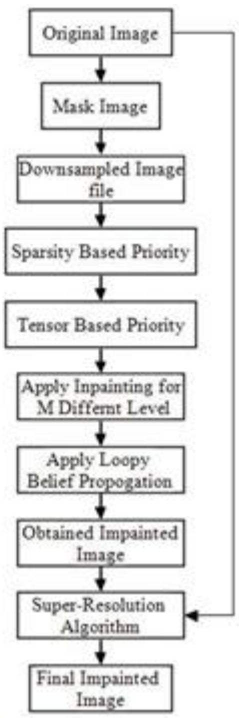

Figure 2: Flowchart of the proposed method.

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TABLE 1: Thirteen configurations used to fill in the unknown parts of the pictures.

Setting	Parameters
1 (default)	Patchs size 55 Decimation factor n=3 Search window 8080 Sparsity based filling order
2	default+rotation by 180 degrees.
3	default+ patchs size 77.
4	default+rotation by 180 degrees+ patchs size 77.
5	Default+patchs size 1111.
6	default+rotation by 180 degrees+ patchs size 1111.
7	default+ patchs size 99.
8	default+rotation by 180 degrees+ patchs size 99.
9	default+ patchs size 99+Tensor based filling order.
10	default+ patchs size 77+Tensor based filling order.
11	default+ patchs size 55+Tensor based filling order.
12	default+ patchs size 1111+Tensor based filling order.
13	default+ rotation by 180 degree+patchs size 99+ Tensor based filling order.

Super-Resolution Algorithm: After the process of inpainting a low resolution image, the single-image super-resolution algorithm is used to reconstruct the high resolution. Process of Super-resolution inpaintig shown in figure3. The texture synthesis at the higher resolution is guided by the use of the low resolution inpainted areas. The main steps involved are:

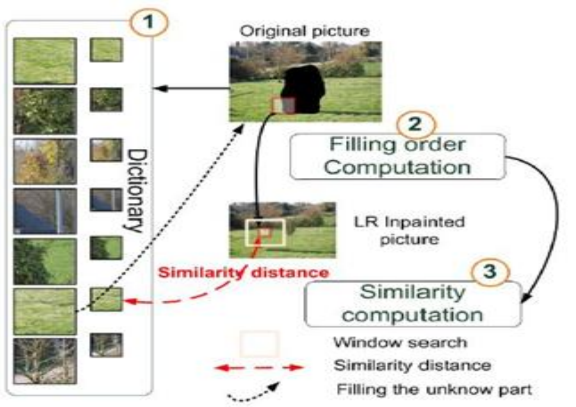

Figure 3: Flowchart of the super-resolution algorithm.

1) Dictionary building: It consists of the correspondence between the low and high resolution image patches. The high resolution and valid patches are evenly extracted from the known part of the image. The size of the dic-tionary is a user-parameter which influence the overall speed/quality trade-off.

2) Filling order of HR image: It is computed by using the sparsity-based method. This improves the quality of the inpainted image compared to other techniques.

3) The case that deals with the LR patch corresponding to the HR patch having the highest priority, its K-NN in the inpainted image of LR are sought.

4) Weight are calculate by using the non-local methods. The distance is used to compute the weight and it is composed of two terms.
a) Patch and its LR neighbors.
b) Distance between the known parts to the HR.

5) The HR image is deduced by linear combination of HR patches with weights previously computed.

6) Stitching: The HR patch is finally placed in the missing area.

V. EXPERIMENTAL RESULTS AND DISCUSSION

This proposed algorithm is implemented in MATLAB 2013a version. This implementation proposes an effective algorithm based on super-resolution image inpainting the mechanism can be used in restoring images with very high resolution or defect ratio. The algorithm is based on the concept of image subdivision and estimation of color variations. Different sizes of blocks which contain noise are inpainted with different levels of surrounding information. Images used for this low resolution colour images. The original image resized to 256x256 and mask size resized to 256x256.This implementation results showed that an almost unrecognizable image can be recovered with visually good result. Result obtained from proposed algorithm shows that the above algorithm further implements fast inpainting technique that will be useful in the case of high resolution pixels. The parameters which are used in above inpainting technique is calculated with first employing basic inpainting method after that Super resolution inpainting is applied results of applying inpainnting are shown in figure 3, figure 4 and figure 5. Formulae for calculating parameters are given below, In following table obtained parameters such as MSE and PSNR shown in table 2 and Table 3,

1) PSNR : Peak signal to noise ratio and it is calculated by using formula.

$PSNR = 10\log_{10}(255 \quad 255=MSE)$

2) MSE- Mean Square Error calculated using formula.

$MSE = sum(sum(X \quad dec)^2))=(M \quad N)$

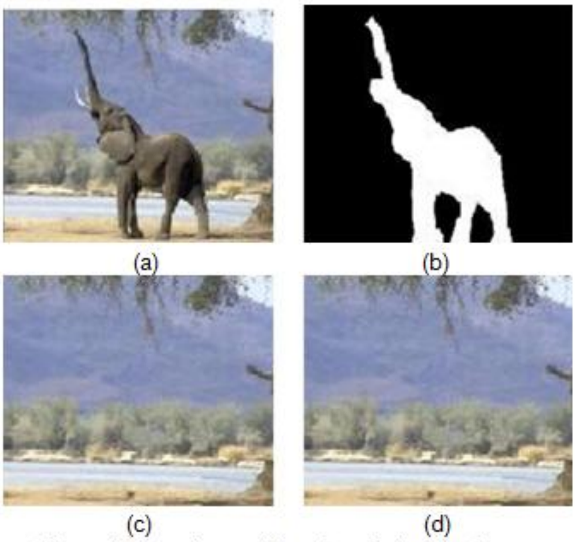

Figure 4: Experimental Results of elephant image (a) Original Image. (b) Mask Image. (c) Inpainting Using Examplar based method. (d) Super Resolution Reconstruction.

TABLE 2: MSE Values

Sr. No.	Image	Examplar Based Method	Super Resolution Algorithm
1	Image1	0.0295	0.0386
2	Image2	0.0185	0.0219
3	Image3	0.0155	0.0289
4	Image4	0.0281	0.0352
5	Image5	0.0179	0.0169
6	Image6	0.0143	0.0154
7	Image7	0.0134	0.0199
8	Image8	0.0060	0.0116
9	Image9	0.0128	0.0207
10	Image10	0.0017	0.0042
11	Image11	0.0017	0.0142

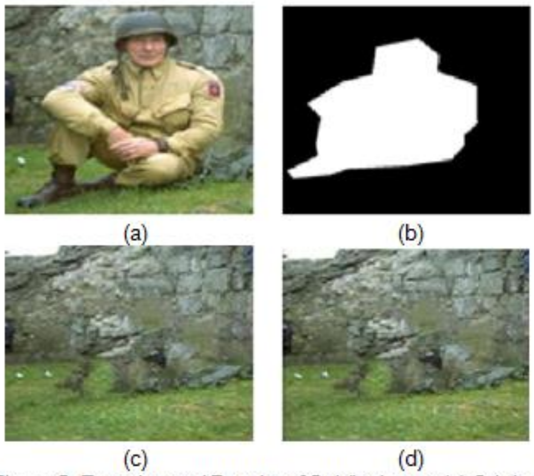

Figure 5: Experimental Results of Soldier image (a) Original Image. (b) Mask Image. (c) Inpainting Using Examplar based method. (d) Super Resolution Reconstruction.

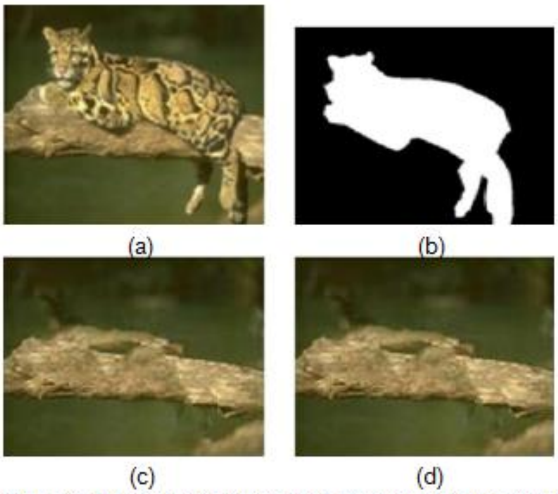

Figure 6: Experimental Results of Tiger image (a) Original Image. (b) Mask Image. (c) Inpainting Using Examplar based method. (d) Super Resolution Reconstruction.

TABLE 3: PSNR Values

Sr. No.	Image	Examplar Based Method	Super Resolution Algorithm
1	Image1	15.3032	14.1371
2	Image2	17.3220	16.5855
3	Image3	18.1024	15.3897
4	Image4	15.5061	14.1371
5	Image5	17.4601	17.7266
6	Image6	18.4409	18.1351
7	Image7	18.7245	17.0106
8	Image8	22.2008	19.3483
9	Image9	18.9428	16.8336
10	Image10	27.7150	18.4669
11	Image11	27.7150	18.4669

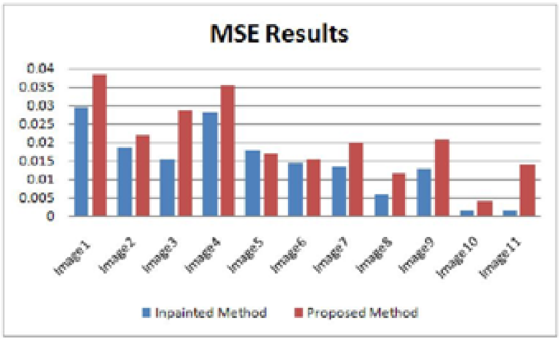

Figure 7: Graphical Comparision of MSE values obtained from Examplar-based Inpainting and Super-Resolution Inpainting.

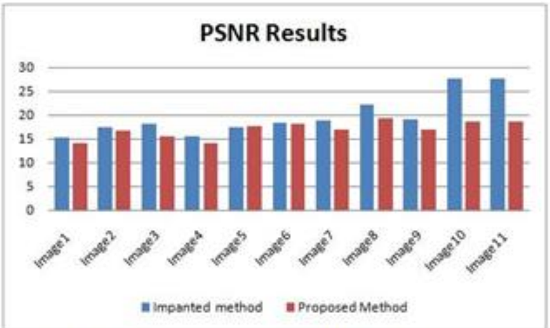

Figure 8: Graphical Comparision of PSNR values obtained from Examplar-based Inpainting and Super-Resolution Inpainting.

CONCLUSIONS

In proposed algorithm we performed several inpainting of the low-resolution images and to fuse them by using a global ob-jective function. After inpainting, a super resolution algorithm is used to improve the visual quality that compares the inten-sity of the neighbour pixels. From result of proposed algorithm it is clear that average MSE for Exempler-Based Inpainting is 0.014491 and average MSE for Super-resolution inpainting is 0.020682, Same average PSNR for Exempler-Based Inpainting is 19.76661818 and average PSNR is 16.93067273. From above values of MSE and PSNR it is clear that hierarchical Super-resolution inpaintig is best suited for high resolution images and main important improvement is likely the use of geometric constraint and higher-level information such as scene semantics in order to improve the visual relevance.

REFERENCES

[1] Olivier Le Meur and Christine Guillemot, “Super-Resolution-based In-painting,” University of Rennes 1, France; INRIA Rennes, France, pp. 1-14.

[2] Dr. P. Sengottuvelan and E. Balamurugan K. Sangeetha, “Combined Structure and Texture Image Inpainting Algorithm for Natural Scene Image Completion,” Journal of Information Engineering and Application, vol. 1, no. 1, pp. 7-12, Feb 2011.

[3] Sachin D Ruikar Vaibhav V Nalawade, “IMAGE INPAINTING USING WAVELET TRANSFORM,” International Journal of Advanced Engineer-ing Technology, vol. 2, no. 4, pp. 302-307, Dec 2011.

[4] A.C. Kokaram, R.D. Morris, W.J. Fitzgerald, P. J. W. Rayner. “Interpo-lation of missing data in image sequences”. IEEE Transactions on Image Processing, Vol. 11, Issue. 4, pp.1509-1519, 1995.

[5] A. Hirani and T. Totsuka. “Combining Frequency and spatial domain in-formation for fast interactive image noise removal”. Computer Graphics, SIGGRAPH 96, PP. 269-276, 1996.

[6] Dongwook Cho and Tien D. Bui,“Image Inpainting Using Waveletbased Intera and Intra-scale Dependency, IEEE Trans. Image Processing,2008.

[7] N.Archana, K.P.Soman S.Padmavathi, “Hierarchical Approach for Total Variation Digital Image Inpainting,” International Journal of Computer Science, Engineering and Applications (IJCSEA), vol. 2, no. 3, pp. 173-182, june 2012.

[8] Mortaza Mokhtari Nazarlu and Javad Badali, “Image Inpainting System Model Based on Evaluation,” International Journal on Computational Sciences and Applications (IJCSA), vol. 3, no. 2, pp. 17-21, April 2013.

[9] Kyungjae Lee, Jaesung Kim, and Sangyoun Lee Jinkyu Hwang, “A Novel Hole Filling Method U sing Image Segmentation-Based Image In-Painting,” in IEEE International Conference on Consumer Electronics (ICCE), Seoul, 2013, pp. 470-471.

[10] Jijina K.Babu Rajani.R,“A Novel Framework for Examplar-Based Inpainting,” INTERNATIONAL JOURNAL OF SCIENTIFIC RE-SEARCH, vol. 3, no. 5, pp. 173-176, May 2014.

[11] Lavanya Vemulapally Girija Vasagiri, “INPAINTING WITH EXTREME FIRMNESS,” International Journal of Advanced Trends in Computer Science and Engineering, vol. 3, no. 1, pp. 231-234, 2014.

[12] P.N. Chatur Sanket Khedikar, “Digital Inpainting on the Basis of Examplar Based Method,” International Journal of Computer Science and

Information Technologies, vol. 5, no. 3, pp. 3943-394, july 2014.

[13] Dr. A. M. Prasad T. Vikram, “Object Removal by Hierarchical Super-Resolution Based Inpainting,” International Journal of Engineering Re-search and Technology (IJERT), vol. 3, no. 9, pp. 16-23, Sept 2014.

[14] Shivamurthy R.C Chetana K M, “A novel approach to Image Inpaint-ing using an Examplar-based method,” IJRIT International Journal of Research in Information Technology, vol. 2, no. 6, pp. 558-562, june 2014.

[15] Sujata Mukherjee, Subhasis Chaudhuri Priyam Chatterjee, “Application of Papoulis-Gerchberg Method in Image Super-resolution and Inpaint-ing,” Oxford University Press on behalf of The British Computer Society., vol. 00, no. 0, pp. 1-9, feb 2007.

[16] K. P. Soman S.Padmavathi, “A Hierarchical Search Space Refinement and filling for Examplar based Image Inpainting,”International Journal of Computer Applications, vol. 52, no. 4, pp. 31-37, aug 2012.

[17] Shanti K. Guru Geeta K. Sarpate, “Digital Image Inpainting Using Patch Priority Based Method,” International Journal of Advance Foundation and Research in Computer (IJAFRC), vol. 1, no. 5, pp. 2398-2400, may 2014.

[18] M. Bertalmio, G. Sapiro, V. Caselles and C. Ballester,“Image inpainting, Computer Graphic (SIGGRAPH 2000), pp. 417424, July 2000.

[19] Criminisi, A., Perez, P., Toyama, K.“ Region filling and object removal by examplar based image inpainting”. IEEE Trans. On Image Processing 13 (2004) 12001212.

[20] A. A. Efros and T.K. Leung, “Texture synthesis by nonparametric sampling, IEEE International Conference on Computer Vision, vol. 2, pp. 10331038, 1999

[21] Xu, Z., Sun, J.“ Image inpainting by patch propagation using patch sparsity.” IEEE TIP 19 (2010) 11531165

[22] O. Le Meur, J. Gautier, and C. Guillemot,“Examplar-based inpainting based on local geometry, in Proc. 18th IEEE Int. Conf. Image Process., Sep. 2011, pp. 34013404.

[23] Y. Wexler, E. Shechtman, and M. Irani, “ Space-time video completion, in Proc. IEEE Comput. Vis. Pattern Recognit., Jun. Jul. 2004, pp. I-120I-127

[24] Jijina K. Babu, Rajani R., “A Novel Framework for Examplar-Based Inpainting, International Journal of Scientific Research, vol. 3, no. 5, pp. 173-176, May 2014.

[25] N. Komodakis and G. Tziritas, “Image completion using efficient belief propagation via priority scheduling and dynamic pruning, IEEE Trans. Image Process., vol. 16, no. 11, pp. 26492661, Nov. 2007.

[26] A. Bugeau, M. Bertalmo, V. Caselles, and G. Sapiro, A comprehensive framework for image inpainting, IEEE Trans. Image Process., vol. 19, no. 10, pp. 26342644, Oct. 2010.

[27] J. Kopf, W. Kienzle, S. Drucker, and S. B. Kang, Quality prediction for image completion, ACM Trans. Graph., vol. 31, no. 6, p. 131, 2012.

[28] K. He and J. Sun, Statistics of patch offsets for image completion, in Proc. 12th Eur. Conf. Comput. Vis., pp. 1629, 2012.

[29] Lavanya Vemulapally Girija Vasagiri, “Inpanting With Extreme Firm-ness, International Journal of Advanced Trends in Computer Science and Engineering, vol. 3, no. 1, pp. 231-234, 2014.

[30] Mounira Ebdelli, Christine Guillemot Olivier Le Meur, “Hierarchical super-resolution-based inpainting,” IEEE Transactions on Image Process-ing, vol. 22, no. 10, pp. 7779-3790, july 2012.

[31] Wenping Wang, Huaiping Yang, and Jiaguang Sun Bin Wang,“Efficient Example-Based Painting and Synthesis of 2D Directional Texture, IEEE Transaction on Visualization and Computer Graphics, vol. 10, no. 3, pp. 268-277, June 2004.

[32] P.N. Chatur, Sanket Khedikar,“Digital Inpainting on the Basis of Ex-ampar Based Method, International Journal of Computer Science and Information Technologies, vol. 5, no. 3, pp. 3943-394, July 2014.

[33] Mortaza Mokhtari Nazarlu and Javad Badali, “Image Inpainting System Model Based on Evaluation, International Journal on Computational Sciences and Applications (IJCSA), vol. 3, no. 2, pp. 17-21, April 2013