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Patch based Inpainting with Refinement of Vicinity Patches using SVD

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ABSTRACT:
Digital image inpainting technique is a means to correct images with an elegant retouching brush. This paper presents a patch-based image inpainting algorithmwith segmentation, multiple patch selection and refinement of selected patches. Patch-based image inpainting algorithm was improved by segmenting the image using K means segmentation to search the candidate patch in relevant source region only. Multiple patches were selected and refined using an efficient patch refinement scheme with higher order singular value decomposition to capture underlying pattern among the candidate source patches. Some patches were selected, out of which few patches were the neighborhood(vicinity) patches and few were the nearest distance patches from the relevant segmentfor a target patch.Vicinity patches were selected in the immediate vicinity of the target region. The best matches for a target patch were mostly found around the patch locality.The threshold for refinement was selected by using minimum and maximum value of standard deviation of the target patch. This eliminated random variation and unwanted artifacts. Segmentation improved patch search in terms of both quality and time.

Keywords: Patch based image inpainting, Neighborhood patches, vicinity patches, Multiple patches, Patch refinement, SVD.

I. INTRODUCTION

Image inpainting is a technique to reconstruct missingregions of an image in such a way that the image appears original to an observer. The main applications include Repairing missing areas in unreliably transmitted images, removing scratches in old photographs, removing text or logos, image zooming, removing undesired objects from an image, or even performing artistic effects. Image inpainting is very significant research area as scientific and cultural heritage of the recent times is preserved in the form photo library.The user needs to identify the missing or missing areas. The user specifiedregion is called inpainting domain.

Inpainting is used as an image editing software. This editing software expect that the user should specify the area to be inpainted and specify the sample that must be put in its place. Digital image inpainting requires the user to specify the area to be inpainted, but fills it automatically using the information available in the surrounding area of the same image.

Patch-based image inpainting algorithms [1-21] are popularly applied for image inpainting problems requiring object removal and region filling. In these algorithms inpainting was performed patch by patch, with structure and texture synthesis. A best patch was selected from the known region and pasted in the missing region. This process was repeated until the entire missing region is inpainted. Modifications in the patch based inpainting techniques were suggested by many authors in formulation of the priority function and finding the best candidate patch using similarity measure for patch selection. Criminisi et al. [1, 3] suggested a priority function that was the product of a data term and confidence term. The confidence term determined the confidence values of the pixels in the known region of the image. The data term was the dot product of the line of equal intensity and the normal at the point on the boundary. This method had a drawback that it cannot handle depth ambiguities and does not reconstruct curved structures.

In order to search the source patch like target patch exemplar-based inpainting algorithms applied a similarity measure such as sum of squared distance (SSD), structure similarity (SSIM), mean squared error (MSE) and perceptually aware mean squared error (PAMSE). The similarity measure was optimised to select the source patches. The target patch was filled in by the source patch. The missing region was inpainted patch-by-patch in an iterative manner by repeating

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the three steps until all the missing pixels were determined.

Le Meur [17] modified data term by adding a tensor term that improved the priority function to represent strong structures. The tensor-based data term was formed with the Eigen values of the structure tensor which helped to propagate the structures effectively.

Gaussian-weighted nonlocal texture similarity measure was suggested in [21] to obtain multiple candidate patches. The refined patch was obtained by α (alpha) trimmed mean filter to inpaint the target region. Deng [22] improved Criminisi's priority term by designing it into two phases. In the first phase the priority was defined by the data term and in the second phase it was defined by the confidence term. The advantage of this method was to propagate geometry of the image to recover textures and structures.The hybrid image inpainting algorithms include image inpainting algorithms based on image segmentation [23-27], image inpainting combining patch-based and PDE-based inpainting. They also combined with multiresolution inpainting and geometric transformation image inpainting algorithms. These algorithms inpaint the texture and structure of an image simultaneously [28-32].

This paper emphasized on patch-based inpainting with multiple patch selection and refinement. The source patches were selected from a relevant source region to reduce time taken for inpainting. The priority of a point to be filled first was calculated based on standard deviation of the patch around target pixel and distance from the center of missing region. similar patches are selected from the source region based on minimum value of sum squared distance.

The selected patches were refined with an efficient patch refinement scheme using higher order singular value decomposition to capture underlying pattern among the candidate source patches. Filtering of multiple patches was used to confine their fundamental pattern by removing artifacts. The threshold for refinement was selected by using minimum and maximum value of standard deviation of the target patch.

The contributions are

(i) Priority calculation based on standard deviation of a patch around a point and distance of the point from the centre of the missing region.
(ii) Segmentation of image pixels with K means segmentation and a segmentation-based patch selection method to find the source patch from a minimized search space.
(iii) A neighborhood patch search method referred as vicinity patch-based on the location and continuity of the image structure.
(iv) Patch selection based on sum squared distance (SSD) between known values of target patch and source patch. Arranging the SSD values in ascending order and selecting first few values. These patches referred as SSD patches
(v) Refine all the selected patches (SSD patches and vicinity patches) to obtain the resultant patch using SVD.

II. PATCH-BASED IMAGE INPAINTING

The user selected area (Region of Interest) is referred as Ω which represents the target region as shown in Fig 1. The source region Φ is the region of the image which contains information to be filled in target region. The boundary between the two is specified as δΩ. The reconstruction is performed from boundary δΩ first and then moved inwards updating δΩ each time. The way in which the δΩ is filled and the way it moves inwards differs in Inpainting algorithms proposed by several researchers. Thus the pixels in Ω are fruitfully assigned values based on a criterion determined by the algorithm until area of Ω becomes zero.

Fig 1 Digital Image Inpainting Problem

III. METHODOLOGY

The priority term was an array of values based on certain criterion that decided the starting point of algorithm. Since the patch being chosen was a square one, the next suitable patch center lied on one of the corners of the square being filled during earlier iteration. For the next cycle higher priority was given to this patch. Hence the patch fill order followed the previous filled patches proceeding and filling the interior of the missing region, moving from boundary towards the center.

In this chapter the priority of the patch to be filled was decided based on the standard deviation of the patch around point 'p' and distance

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of the point from the center of the missing region.The priority term was evaluated for all the points on the boundary. The patch on the boundary having highest priority was the target patch.

The input image was divided into groups using K means segmentation. The value of K was set as three, hence the image was divided into three groups. A higher value of the standard deviation implied that the patch was on the edge belonging to the different groups. On the other hand, a lower value would mean that it belonged to only one group or all pixels are similar. In terms of K means the patch with higher value of standard deviation contained the pixels belonged to multiple groups and lower deviation belonged to one group.

The priority of patch was taken based on inverse of standard deviation so that filling of the patch was done with either foreground or the background pixels. The distance of a pointp from the centre of the missing region was taken as another parameter in the priority term so that a point which was further away from the center of the missing region was given higher priority. Thus, the far ends of longer section of the damage were given higher priority. The new fill order was decided by the combination of the standard deviation of a patch and its distance from center of damage/missing region.The priority term was defined as

$$\mathrm{priority}(p) = \frac{1}{\sigma_p} + \|d\| \forall \quad p \in \delta\Omega \qquad (1)$$

$$d = \sqrt{((y - y_r)^2 + (x - x_c)^2\,)} \qquad (2)$$

$\sigma_p$was the standard deviation of a patch around p and pis the center pixel of the patch, (x, y) were the coordinates of point p and distance d was normalized using d_{max}. The coordinates y_r and x_c were defined by

$$y_r = \frac{y_{min} + y_{max}}{2}\ ,\ x_c = \frac{x_{min} + x_{max}}{2} \qquad (3)$$

In the above equation x_c was column coordinate of center of the missing area, $y_r$was row coordinate of center of the missing area, and (x_{min} ,y_{min}) and (x_{max} ,y_{max}) minimum and maximum coordinates of the boundary pixels dΩ.

dΩwas obtained by convolving fill region $F_g$with the mask function. The fill region F_g was a matrix of same size as image having one in the target region and zero in the source region. The fill region was the region identified by the user and mathematically represented as

$$F_g = \begin{cases} 1, & p \in \Omega \\ 0, & p \in \Phi \end{cases} \qquad (4)$$

The boundary region $\delta\Omega$ was determined by convolving F_g with M where M was the mask function used for edge detection given by equation,

$$\delta\Omega = F_g * M \qquad (5)$$

Where M was

$$M = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -8 & 1 \\ 1 & 1 & 1 \end{bmatrix} \qquad (6)$$

The distances in equation 1 are normalized using maximum distance d_{max} which was calculated as

$$d_{max} = \sqrt{(y_{max} - y_r)^2 + (x_{max} - x_c)^2} \qquad (7)$$

The standard deviation σ_p of patch was calculated by considering all the pixels of patch in case. While evaluating the standard deviation the known pixels in a patch are considered. The unknown pixels were having value as zero which was a convention used by most of the inpainting algorithms. The patch at the boundary having highest priority defined by equation 1 was the target patch.

The fill order is chosen to begin with most suitable pixel and fill the complete exterior border first and moving inwards in circular manner during the next iterations.

As it goes with the property of standard deviation that higher deviation would cover more groups and hence much of information to be restored first if standard deviation is directly proportional to priority, that the patch with higher standard deviation are chosen as first priority to fill, all of the pixels lying on borders of the background and foreground will be filled in a stretch.

3.1 K MEANS SEGMENTATION FOR IMAGE INPAINTING

The input image with missing pixels was segmented using K-means segmentation. The source patches were selected from the segment into which the target patch belongs to. This reduced the time needed for patch selection and improved the performance of inpainting. The advantage of segmentation was that selection of good patches by discarding of improper patches.In patch-based methods the target patches were filled in sequential manner from the boundary towards the center of damage. The interior patch selection depends on the boundary patches. The interior patches were selected based on a neighborhood of the boundary patches. K_n similar patches were selected and refined by using HOSVD.

3.2HOSVD FOR REFINEMENT

The selected source patches were refined by using higher order singular value decomposition (HOSVD). The source patches were chosen based on known values in target patch. This helped patch refinement technique of selected source patches to confine the interior details amongst them for the target patch. HOSVD was used to extract core information from multi-dimensional data due to its high performance and simple implementation.

A patch from the source region was selected based on minimum distance in each of its constituent components from the target patch. In this work patch refinement was based on HOSVD which enabled multiple feature inputs to select prominent features. The algorithm selected K_n nearest distance patches for each target patch. This added to the execution time, as a counter effect the search space was limited to a specific region only. The search area was limited to the segment to which the center pixel p of the target patch belonged to which reduced significantly. The K means segmentation was implemented based on the center of group reference. If the image was divided in Kgroups then Kreference centers were chosen and initial classification of each pixel was made and labeled as per sum of square distance of each pixel from the reference as in equation 8.

$G = \{g \in \Phi : {}_{argmin}\, d(C_q\ ,\ C_g) \forall\ C_q \in \Phi\}$ (8)

In the above equation$C_q$is the center of patchΨ_q, C_g is the center of group g and $g \in 1,2 \ldots . K$. For each target patch$K_n$patches were selected from G to which the centre point p of the target patch belonged to. The selected nearest K_n patches were padded in extended columns.

$Z = [P_1, P_2\ , P_3 \ldots \ldots . P_{K_n}]$ (9)

The dimensionality of Z matrix had w rows wK columns and d as depth for colors. However, HOSVD was implemented by SVD in all these dimensions. Since SVD for two dimensional matrices was available readily, the algorithm transformed Z matrix in to two dimensions. The size of this matrix was transformed into two dimensions depth wise, row wise and column wise. The transformed matrices were represented by equation 10.

$a_i = T\{Z\},\ where\ \ i = 1,2,3$ (10)

a_i was resulting two-dimensional matrix with transformation$T$. For the transformed matrices, SVD was determined by

$[U_i, S_i, V_i] = SVD(a_i),\ \ \ where\ i = 1,2,3$
(11)

Here $S_i$was the matrix with singular values. The columns of U_i were the left singular vectors ofS_i, whereas those of V_i were right singular vectors. To filter out$S_i$values and select only the specific range, two thresholds were obtained from r_1 as lower limit and r_2 as upper limit. The singular values provided main information about the source patches. The source patches selected for a target patch were almost similar, most of the coefficients were either zero or very small and only a few were large. The larger coefficients carried the major information about the patches; smaller coefficients provided fine texture details of the patches. Hence the larger coefficient captured the core information (structural details) of the patches which must be retained.

Selection of the lower range signified the smoothness of the pixel variation in a patch, and a lower standard deviation implied smooth variations. Smoothness was also related to the lower values of the S_i matrix. Hence the lower range r_1 was taken to be least of the patch deviations around the damage. Since standard deviation was the value obtained with respect to the mean of a variable. Lower and upper threshold were found around the mean of the S_i matrix. The threshold values were defined by equation (12) and (14). The upper threshold t_2 was

$t_2 = mean(S_i) \times r_2$ (12)

$r_2 = max(\sigma_p),\ \forall\ \ P \in Z$ (13)

Where $\sigma_p$is standard deviation of patch P and there are K_n similar patches. The lower threshold t_1 was

$t_1 = mean(S_i) \times r_1$ (14)

$r_1 = min(\sigma_p),\ \forall\ P \in Z$ (15)

The lower and upper threshold values affect the selection of singular values of S matrix of SVD. Sharp edges of the structure were available in higher singular values. The lower end values of S matrix constituted smoothness, and far smooth values induced errors. Therefore, a substantial lower cut off was necessary to eliminate the smooth values. This was done by elimination of the zero values elements of the S matrix and corresponding left and right vectors, U and V. The filtered rows and columns of the singular values were obtained by rejecting/eliminating singular values lower than threshold t_1 and higher than the upper threshold t_2. Bandwidth of the filter was r_2-r_1.

$S_{f\,i} = \begin{Bmatrix} S_i : t_1 < S_i < t_2 \\ 0, : otherwise \end{Bmatrix}$ (16)

Reconstruction of the matrix from the above gave the values that were refined and selected. The equation for reconstructing the matrix was given by

$b_i = \ u_i S_{f\,i} v'_i wherei = 1,2,3$(17)

In this equation u_i and v_i was the modified left and right vectors, U and V. The data thus obtained had a matrix for each dimension; a reverse transform to original dimensionality of the original data was from the average of the reconstructed data matrices.

$A = \frac{\sum_{i=1}^{3} b_i}{3}$ (18)

This refined patch to be pasted was obtained by using equation 18.

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3.3 VICINITY PATCHES

Vicinity patches were selected in the immediate vicinity of the target region. The best matches for a target patch were mostly found around the patch locality. Hence the search area was limited to a smaller region around the missing area instead of whole of the image. The purpose was to restrict the search to the locality of likelihood and reduced execution time notably. The vicinity patches were selected from the neighborhood of the target patch such that one corner of the vicinity patch overlaps with a known pixel in the target patch. Therefore, minimum of one and maximum of three vicinity patches can be extracted from the source region. These vicinity patches lie on the diagonally opposite side of the missing pixels of target patch. This was achieved by varying row and column in all four directions excluding missing part with the help of fill region F_g.

Let (x_0, y_0) be the centre of target patch, (x_v, y_v) be the center of vicinity patch and w be the parameter used to set patch width (patch width $= 2 * w + 1$). The centers of all vicinity patches are obtained using equation 19.

$$(x_v, y_v) = (x_0 \pm v, y_0 \pm v) \forall\ (x_v, y_v) \in \Phi \quad (19)$$

v is the patch width. Hence the process will form to be the continuation of the structure that was opposite to the missing part of pixels. V_{n1} number of patches were the neighborhood (vicinity) patches selected for a target patch.

Proposed KNN-KV-SVD algorithm

Input: An input image with inpainting domain Ω.
Output: An output image with the inpainting domain filled in

1. Repeat until there are missing pixels in Ω.
2. Locate boundary δΩ, and calculate $\text{priority}(p)$ using equation (1) for all pointsp inδΩ.
3. Obtain point p with highest value of priority and target patch around pointp
4. Find multiple (V_{n1}) similar source vicinity patches.
5. Find multiple (K_{n2}) SSD similar patches.
6. Total multiple patches $K_{m=} V_{n1}+K_{n2.}$
7. Filter K_m multiple similar patches using SVD as discussed in section 3.2 to obtain one refined patch
8. Update the unknown pixels in target patch with known pixels in refined patch.

IV. SIMULATION AND RESULT ANALYSIS FOR KNN-KV-SVD ALGORITHM

The algorithm discussed in this paper is based on multiple patch selection and refinement using SVD. The algorithm is written in MATLAB and executed on a system with Processor: Intel i5 CPU@2.40GHz, memory (RAM): 4.00GB, and 64-bit operating System. Original color images of size 256 x 256 from JT database and BIS dataset were used for testing the algorithm. The region to be inpainted or the object to be removed was identified by the user. In order to test the algorithm damages were created of various shape and size at different spatial locations in the image.The performance of proposed algorithm was compared with algorithm discussed in paper [35]. The performance parameters are tabulated in table 1 for Deng [22], Ding [21], Criminisi [1], IDTA, GRAD, KP discussed in paper[34], KNN-KV-Alpha [35], KNN-SVD discussed in paper [36] and proposed algorithm.

4.1 DAMAGE INPAINTING

The output images for various input images with inpainting domain identified are shown in figure 2. In the figure 2 row-1 shows the original image, row-2 shows missing image, row-3 is Deng output,row-4 is Ding output, row-5 Criminisi output, row-6 is IDTA output. The quality factors for output image-1 to image-3 are indicted in table 1. Proposed KNN-KV-SVD algorithm's quality factor for image-1 is improved by 12.77% with respect to Deng algorithm. Time required for inpainting with KNN-KV-SVD algorithm is reduced by 36.45% as compared with Criminisi algorithm for image-1. Proposed KNN-KV-SVD algorithm and KNN-KV-Alpha algorithm take less time for inpainting because the similar source are found in the vicinity of missing area

From the tabulated results it is observed that KNN-KV-SVD works better than KNN-KV-Alpha. KNN-KV-Alpha takes less time as compared to alpha trimmed method (Ding), also KNN-KV-SVD takes less time as compared to KNN-SVD. This is because the similar patches are searched about the missing region. That is similar patches are found in the vicinity of the missing region (vicinity patches).

In the figure 3 row-1 shows the original image, row-2 shows missing image, row-3 is KNN-KV-Alpha output,row-4 is GRAD output, row-5 KP output, row-6 is KNN-SVD output, and row-7 is proposed KNN-KV-SVD output.

4.2 RESULTS OF KNN-KV-SVD FOR 100 IMAGES

The quality factor of inpainted images for Deng, Ding, Criminisi, GRAD, KP, IDTA, KNN-KV-alpha, KNN-SVD and KNN-KV-SVD algorithms was tested for 100 images and the

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quality factor for these images is represented in figure 2.

The quality factors are plotted with x-axis indicating image number and y-axis indicating quality factor. The quality factor of KNN-KV-SVD algorithm is better than all other algorithms for most of the images. Figure shows a green colored line for proposed KV-SVD algorithm.

4.3 FAILURE CASES

TheFailure Cases KNN-KV-SVD Algorithm are shown in figure5. The algorithm performed effectively for removing the objects and for damage inpainting, but failed for the images shown. The algorithms failed to inpaint due to large missing area and multiple significant edges.

V. CONCLUSION

The proposed KNN-KV-SVD algorithm performed better than the other methods like KNN-KV-Alpha, KNN-SVD and IDTA algorithm. KNN-KV-SVD algorithm reduced the time needed for inpainting because vicinity patches along with segmentation patches are used for filtering. The number of vicinity patches is less than segmentation patches as too many vicinity patches tend to blur the filtered target patch.

REFERENCES

[1]. A. Criminisi, P. Perez, and K. Toyama, “Object removal by exemplar-based inpainting", in IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2003. Proceedings, p.p. II721-II728, 2003.

[2]. Z. Xu and J. Sun, “Image inpainting by patch propagation using patch sparsity”, IEEE Transactions on Image Processing, vol. 19, no. 5, p.p. 1153-1165, May 2010.

[3]. A. Criminisi, P. Perez, and K. Toyama, “Region filling and object removalby exemplar-based image inpainting”, IEEE Transactions on Image Processing, Vol. 13, NO. 9, p.p. 1-13, Sep 2004.

[4]. N. M. V. Couto, “Inpainting based image coding: a patch-driven approach”, M. S. thesis, Tech. Univ. of Lisbon, Lisbon, Portugal, p.p. 1952-1956, Oct. 2010.

[5]. R. M. Noriega, A. Roumy, and G. Blanchard, “Exemplar-based image inpainting: fast priority and coherent nearest neighbor search”, IEEE International Workshop on Machine Learning for Signal Processing (MLSP), p.p. 1-6, Sep. 2012.

[6]. J. Wu and Q. Ruan, “Object removal by cross isophotes exemplar-based image inpainting”, in 18th International Conference on Pattern Recognition (ICPR'06), p.p. 810-813, 2006.

[7]. J. Chhabra and V. Birchha, “Detailed survey on exemplar based image inpaintingtechniques”, International Journal of Computer Science and Information Technologies, vol. 5, no. 5, p.p. 6350-6354, 2014.

[8]. T. T. Dang, C. Larabi, and A. Beghdadi, “Multi-resolution patch and window-based priorityfor digital image inpainting problem”, in 3rd International Conference Image Processing Theory, Tools and Appl, 2012, p.p. 280-284, 2012.

[9]. B. Wohlberg, “Inpainting by joint optimization of linear combinations of exemplars”, IEEE Signal Processing Lett, vol. 18, no. 1, p.p. 75-78, Jan. 2011.

[10]. A. Wong and J. Orchard, “A non local-means approach to exemplar-based inpainting”, in Proc. IEEE International Conference Image Process, p.p. 2600-2603, 2008.

[11]. Z. Lu, H. Huang, L. Li, and D. Cheng, “A novel exemplar-based image completion scheme with adaptive TV constraint”, in Proc. 4th International Conference Genetic and Evolutionary Computing, p.p. 94-97, 2010.98

[12]. P. Arias, G. Facciolo, V. Caselles, and G. Sapiro, “A variational framework for exemplarbased image inpainting”, International JOURNAL Computer Vision, vol. 93, no. 3, p.p. 319-347, Jul. 2011.

[13]. J. Wang, K. Lu, D. Pan, N. He, and B. Bao, “Robust object removal with an exemplar-based image inpainting approach”, Neurocomputing, vol. 123, pp. 150-155, Jan. 2014.

[14]. V. Kumar, J. Mukherjee, and S. K. D. Mandal, “Image inpainting through metric labeling via guided patch mixing”, IEEE Transactions Image Processing, vol. 25, no. 11, p.p. 5212- 5226, Nov. 2016.

[15]. T. Ruzic and A. Pizurica, “Context-aware patch-based image inpainting using Markov random field modeling”, IEEE Transactions Image Processing, vol. 24, no. 1, p.p. 444-456, Jan. 2015.

[16]. Y. Liu and V. Caselles, “Exemplar-based image inpainting using multiscale graph cuts”, IEEE Transactions Image Processing, vol. 22, no. 5, p.p. 1699-1711, May 2013.

[17]. O. L. Meur, J. Gautier, and C. Guillemot, “Examplar-based inpainting based on local

geometry", in Proc. 18th IEEE International Conference Image Process, p.p.3401-3404, 2011.

[18]. P. Buyssens, M. Daisy, D. Tschumperle, and O. Lezoray, "Exemplar-based inpainting: technical review and new heuristics for better geometric reconstructions", IEEE Transactions Image Processing, vol. 24, no. 6, p.p. 1809-1824, Jun. 2015.

[19]. C. Barnes, E. Shechtman, A. Finkelstein, and D. B. Goldman, "PatchMatch: a randomized correspondence algorithm for structural image editing", ACM Transactions Graphics, vol. 28, no. 3, p.p. 24-1, Aug. 2009.

[20]. J. H. Lee, I. Choi, and M. H. Kim, "Laplacian patch-based image synthesis", in Proc. IEEE Computer Vision and Pattern Recognition, p.p. 2727-2735, 2016.

[21]. D. Ding, S. Ram and J. J. Rodriguez, "Image Inpainting Using Nonlocal Texture Matching and Nonlinear Filtering", IEEE Transactions On Image Processing, Vol. 28, No. 4, p.p. 1-14, April 2019.

[22]. L-J Deng,T-Z Huang,X-L Zhao (2015),"Exemplar-Based Image Inpainting Using a Modified Priority Definition", PLOS ONE | DOI:10.1371/journal.pone.0141199, p.p. 1-18, October 22, 2015

[23]. O. L. Meur, J. Gautier, and C. Guillemot, "Super-resolution-based inpainting", in Proc. 12th European Conference Computer Vision, p.p. 554-567, 2012.

[24]. E. T. Hassan, H. M. Abbas, and H. K. Mohanmed, "Image inpainting based on image segmentation and segment classification", in Proc. IEEE International Conference Control Syst. Computer Eng., p.p. 28-33, Nov. 2013. 99

[25]. S. Kahali, M. Ghorai, and S. S. Thakur, "Image inpainting based on segmentation for relevant patch selection", in Proc. International Conference Computer Comm. Manuf., p.p. 22-28, 2014.

[26]. T. Liu, X. Tian, Q. Wang, S. Shao, and X. Sun, "Image inpainting algorithm based on regional segmentation and adaptive window exemplar", in Proc. International Conference Adv. Computer Control, p.p. 656-659, Mar. 2010.

[27]. R. Zhang, Q. Chen, Z. Miao, and Z. Tang, "Image inpainting based on image segmentation", in Proc. International Conference Wireless Mobile Multimedia Networks, p.p. 315-318, Sep. 2010.

[28]. M. Shen and B. Li, "Structure and texture image inpainting based on region segmentation", in Proc. IEEE International Conference Acoust. Speech Signal Process, p.p. I701-I704, Apr. 2007.

[29]. H. Grossaner, "A combined PDE and texture synthesis approach to inpainting", in Proc. European Conference Computer Vision, p.p. 214-224, 2004.

[30]. A. Bugeau and M. Bertalmio, "Combining texture synthesis and diffusion for imageinpainting", in Proc. International Conference Computer Vision Theory Appl., p.p. 26-33, 2009.

[31]. S. Hesabi, M. Jamzad, and N. Mahdavi-Amiri, "Structure and texture image inpainting", in Proc. International Conference Signal Image Processing, p.p. 119-124, Dec. 2010.

[32]. M. Bertalmio, L. Vese, G. Sapiro, and S. Osher, "Simultaneous structure and texture image inpainting", IEEE Transactions Image Processing, vol. 12, no. 8, p.p. 882-889, Aug. 2003.

[33]. L. Cai and T. Kim, "Context-driven hybrid image inpainting", IET Image Processing, vol. 9, no. 10, p.p. 866-873, Sep. 2015.

[34]. A. S. Awati and M.R. Patil, "Image Inpainting using Exemplar based Technique with Improvised Data Term", CTEMS - 2018, IEEE Xplore: 25 July 2019, DOI: 10.1109/CTEMS.2018.8769238.

[35]. A. S. Awati and M. R. Patil , "Inpainting with Refinement of Vicinity Patches using alpha trim filter for Heritage Sites" in International Journal of Current Engineering and Technology volume 9, issue 2, p.p. 226-233, March/April 2019, E ISSN 2277–4106, P ISSN 2347 5161©2019 INPRESSCO, DOI: https://doi.org/10.14741/ijcet/v.9.2.5.

[36]. Anupama S Awati , Meenakshi R. Patil , "Inpainting of Structural Reconstruction of Monuments Using Singular Value Decomposition Refinement of Patches", International Journal of Image, Graphics and Signal Processing(IJIGSP), volume 11, issue 5, pp. 44-53, Published Online May 2019 in MECS, DOI: 10.5815/ijigsp.2019.05.05, (http://www.mecs-press.org/).

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Table 1
Performance Parameters of Proposed KNN-KV-SVD Algorithm for Image-1 to Image-4

Image-1 Performance Parameters of for a Missing Area 1.2405%										
Algorithm	**Q**	**SNR**	**SS**	**L**	**MSE**	**XK**	**NAE**	**AD**	**SC**	**T**
Deng	44.93	45.22	0.9951	1	1.0000	0.9999	0.9989	0.9998	0.9998	32.81
Ding	40.86	41.33	0.9922	1	1.0000	0.9995	0.9986	0.9991	0.9993	147.16
Criminisi	44.62	44.86	0.9959	1	1.0000	1.0001	0.9991	0.9997	0.9997	35.80
IDTA	43.80	44.09	0.9962	1	1.0000	1.0004	0.9990	0.9989	0.9991	33.76
GRAD	43.73	44.09	0.9950	1	1.0000	0.9996	0.9990	0.9991	0.9993	33.64
KP	39.88	40.38	0.9920	1	1.0000	0.9993	0.9986	0.9987	0.9990	34.92
KNN-KV-Alpha	46.08	45.83	1.0000	1	1.0001	0.9992	0.9996	0.9996	0.9953	16.91
KNN-SVD	45.84	46.08	0.9961	1	1.0000	1.0001	0.9992	0.9996	0.9996	31.89
Proposed	46.08	45.83	1.0000	1	1.0001	0.9992	0.9996	0.9996	0.9953	22.75
Image-2 Performance Parameters for a Missing Area 1.1414%										
Algorithm	**Q**	**SNR**	**SS**	**L**	**MSE**	**XK**	**NAE**	**AD**	**SC**	**T**
Deng	36.21	36.93	0.9916	1	0.9999	0.9975	0.9983	0.9967	0.9962	30.82
Ding	37.40	38.20	0.9914	1	0.9999	0.9972	0.9972	0.9980	0.9953	116.71
Criminisi	37.03	37.66	0.9931	1	0.9999	0.9977	0.9976	0.9984	0.9965	32.74
IDTA	36.06	36.78	0.9932	1	0.9999	0.9970	0.9971	0.9976	0.9953	32.96
GRAD	35.71	36.43	0.9931	1	0.9999	0.9970	0.9970	0.9977	0.9953	33.31
KP	36.73	37.42	0.9929	1	0.9999	0.9974	0.9973	0.9980	0.9959	33.55
KNN-KV-Alpha	38.36	37.76	1.0000	1	0.9979	0.9978	0.9985	0.9967	0.9987	17.35
KNN-SVD	37.77	38.35	0.9937	1	1.0000	0.9979	0.9978	0.9985	0.9967	27.40
Proposed	38.36	37.77	1.0000	1	0.9979	0.9978	0.9985	0.9967	0.9968	25.08
Image-3 Performance Parameters for a Missing Area 0.8484%										
Algorithm	**Q**	**SNR**	**SS**	**L**	**MSE**	**XK**	**NAE**	**AD**	**SC**	**T**
Deng	42.22	42.30	0.9988	1	1.0000	0.9999	0.9994	0.9999	0.9999	28.73
Ding	39.62	39.81	0.9982	1	1.0000	0.9995	0.9992	0.9991	0.9993	84.93
Criminisi	44.59	44.65	0.9994	1	1.0000	0.9999	0.9997	0.9998	0.9999	33.74
IDTA	42.82	42.91	0.9992	1	1.0000	0.9998	0.9996	0.9996	0.9997	32.31
GRAD	42.44	42.53	0.9991	1	1.0000	0.9998	0.9996	0.9996	0.9997	32.62
KP	39.24	39.42	0.9984	1	1.0000	0.9995	0.9994	0.9989	0.9992	34.29
KNN-KV-Alpha	42.51	42.40	1.0000	1	0.9998	0.9995	1.0000	0.9998	0.9954	21.80
KNN-SVD	42.41	42.50	0.9986	1	1.0000	0.9998	0.9995	1.0000	0.9998	29.06
Proposed	42.51	42.41	1.0000	1	0.9998	0.9995	1.0000	0.9998	0.9978	23.52

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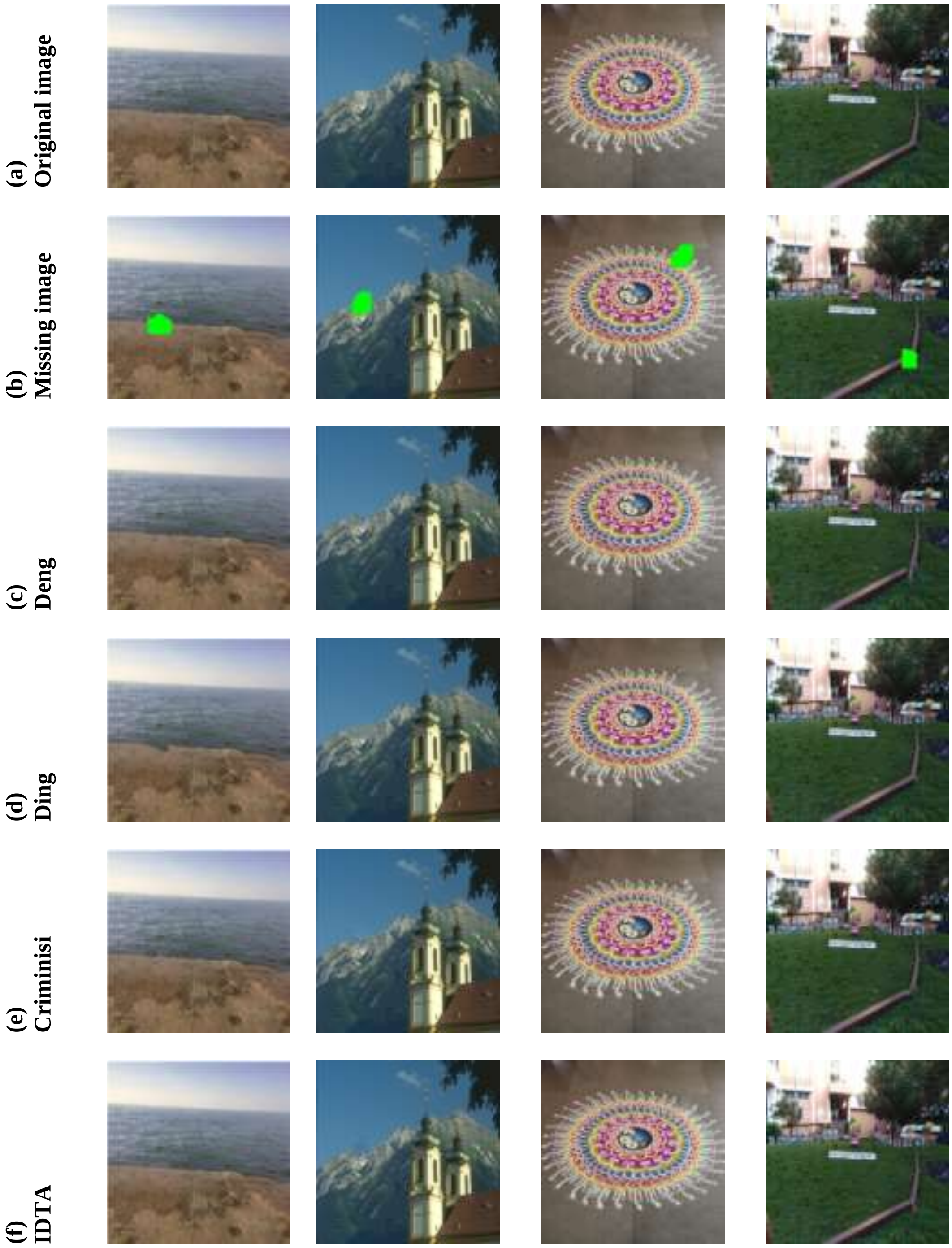

Image-1 Image-2 Image-3 Image-4

Fig 2 a) Original Image (b) MissingImage Inpainting results—
(c) Deng Algorithm (d)Ding Algorithm (e) Criminisi Algorithm (f)IDTA Algorithm

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Fig 3 a) Original Image (b) Missing Image (c) KNN-KV-AlphaAlgorithm(d) GRAD Algorithm (e) KP Algorithm(f) KNN-SVD Algorithm (g) KNN-KV-SVD Algorithm

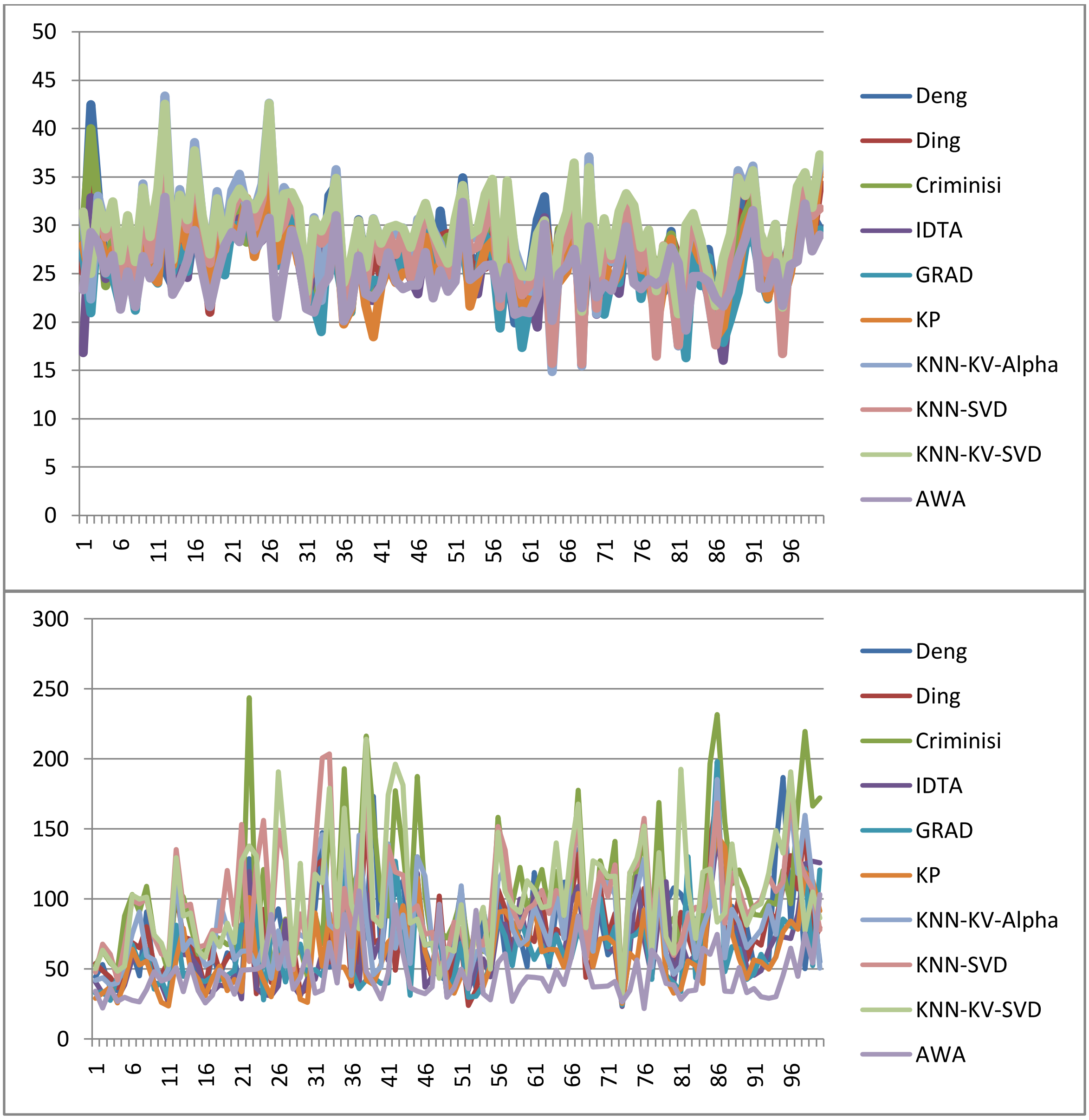

Fig 4Comparison of Quality Factor and Time for 100 Images

Fig 5Failure Cases of KNN-KV-SVD