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PERFORMANCE ANALYSIS OF IMAGE INPAINTING WITH JOINT FILTERING OF MULTIPLE PATCHES USING SVD AND ALPHA TRIMMED FILTER

Anupama S Awati*1, Meenakshi R. Patil*2

*1Dept Of E&C, KLS GIT, Belgaum, India.

*2IEEE Member, Dept Of E&C, CMR Institute Of Technology Bangalore, India.

ABSTRACT

Image inpainting is a smart editing tool. The patch-based algorithms inpainted the damaged/missing region patch by patch propagating from the boundary towards the center of the missing region. Several patch-based image inpainting methods relied on single patch selection and few on multiple patch selection-based method. Multiple source patches were used to obtain a more similar source patch for the target patch. Since the single source patch was chosen based on partially known target patch, a large variation resulted in artifacts in the inpainted region. To overcome it, multiple source patches were selected and filtered jointly to capture the core pattern amongst them. The resultant filtered patch was an optimal patch for the corresponding target patch. This paper compared the performance of joint filtering of SVD values of similar patches(KNN-SVD)and filtering of similar patches using alpha trimmed filters(KNN-KV-Alpha).These two algorithms were tested and evaluated for input images and results were compared with standard algorithms. Results showed that the time required for inpainting was drastically reduced while the quality factor was equivalent with the existing techniques. KNN-KV-Alpha gave high quality factor with less time for inpainting as compared to KNN-SVD as the similar patches were selected in the neighbourhood of the missing region.

Keywords: Inpainting; Improvised Data Term, Singular Value Decomposition Refinement Of Similar Patches, Vicinity Patches, Adaptive Patch Size, Sequencing Of Patch Priorities, Standard Deviation As Patch Priority, Multiple Patch Selection**.**

I. INTRODUCTION

Patch-based image inpainting algorithms [1] have been introduced to address image inpainting problems for object removal and region filling. These algorithms inpaint the damaged region patch by patch with structure and texture synthesis. These algorithms had three steps which were iterative, location of the target patch, search of the best candidate patch and alteration of the target patch with the corresponding pixels from the source patch [2]. Many variations had been suggested in formulation of priority function and search of the best candidate patch. Many authors had suggested variations in calculation of priority function and similarity measure for patch selection. Criminisi et al [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 calculated the dot product of the line of equal intensity and the normal at the point on the boundary. The method did not reconstruct curved structures. In order to search the source patch similar to target patch, patch-based inpainting algorithms applied a similarity measure such as sum of squared distance (SSD) [4], structure similarity (SSIM), mean squared error (MSE), gradient components [6], statistics of patch offsets [5] and perceptually aware mean squared error (PAMSE).The similarity measured was optimised to select the source patches. The target patch was filled in by the source patch. The damaged region was inpainted patch-by-patch in an iterative manner by repeated steps until all the damaged pixels were determined [7, 8].V Sairam et al [9] suggested a modification in patch match criteria with difference in gradient of source patch and target patch along with sum squared distance. The authors also devised an algorithm for inpainting with gradient of image as a data term. Meur et al [10] modified data term with a tensor term that improved the priority function to represent strong structures. The tensor-based data term formed with the Eigen values of the structure tensor helped propagation of the structures.

Gaussian-weighted nonlocal texture similarity measure was suggested in [11] to obtain multiple candidate patches. The refined patch was obtained by α (alpha) trimmed mean filter to inpaint the target region.Deng et al [12] improved Criminisi's priority term with 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 algorithm propagated geometry of the

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image and recovered textures and structures. Meur et al [13] suggested down-sampling of the input image and inpainted the lowest resolution image with different patches with loopy belief propagation.Zhang et al [14] designed a method to assign the priority and guidelines for filling order. The priority was assigned with color distribution analysis instead of isophotes driven priority method. Higher priority was given to the structures which maintain the consistency of texture and continued edges for a better visual quality.Qian et al [15] suggested which improved Criminisi algorithm with adaptive sample size and selected multiple similar source patches. The authors developed inpainting based on patch sparsity made the patch width adaptive to the input image.

1. Background

For a given image I, the object to be removed or area to be inpainted was manually marked by the user and referred as inpainting domain Ω. The pixels in the target region Ω are the unknown pixels and the pixels in source region Φ are known pixels. The boundary between Φ and Ω was denoted as δΩ as depicted in figure 1. After each iteration of the algorithm Ω shrank and was updated. The point p had the highest priority, as this point lied on the edge between green and blue region. A target patch was an image segment of square shape and of size wxwacross pointp. A patch identical to target patch was identified from the source region using distance measurements. The similar patches to target patch were$\Psi_{q'}$ and $\Psi_{q''}$,as shown in figure 1.

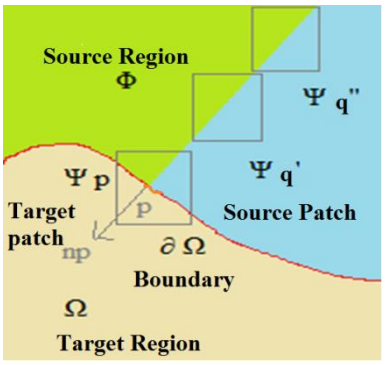

Fig 1: Patch-Based Image Inpainting

The block diagram representation of image inpainting technique is described in figure 2. The input image was an image with missing pixels. The user selected the damaged/target region in the image to be inpainted. The target region was filled by using patches from the source region. Pixels in the missing region were filled by progressively propagating information from outside the boundary towards the center of the damaged region. Patch-based inpainting technique was achieved by searching a similar patch from the source region and pasting it in the target region. The entire region was filled by repeating the same procedure.

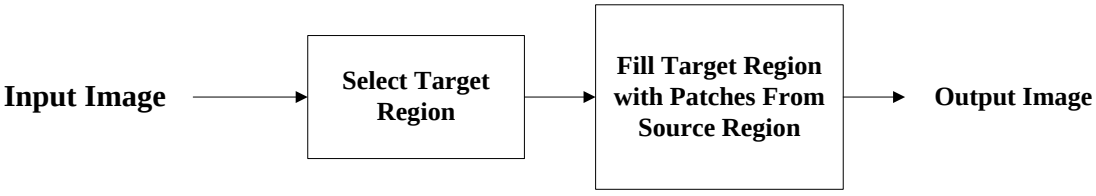

Fig 2: Block Diagram of Patch-Based Image Inpainting Technique

2. The Priority Term

The priority of the patch to be filled was decided based on the standard deviation of the patch around point 'p'and distance 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 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 damaged region was taken as another parameter in the priority term so that a point which was further away from the centre of the damaged 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

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

where

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

In equation 2 $\sigma_p$was the standard deviation of a patch around p andp is 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

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

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

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

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

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

Where M was

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

The distances in equation 2 are normalized using maximum distance d_{max}which was calculated as

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

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 2 was the target patch.

3. Image Segmentation and Patch Selection

The damaged image was segmented using K means segmentation. K means segmentation helped in selecting the source patches from relevant segment or group, to reduce time required in searching a similar patch. K means aided in reliable patch selection discarding many improper source patches leading to good quality patches. A patch was selected from a group based on the point of highest priority. If this point belonged to a group then, similar patches from that group were selected by considering minimum distance between the known values of pixels in the target patch.

4. KNN-KV-Alpha Algorithm

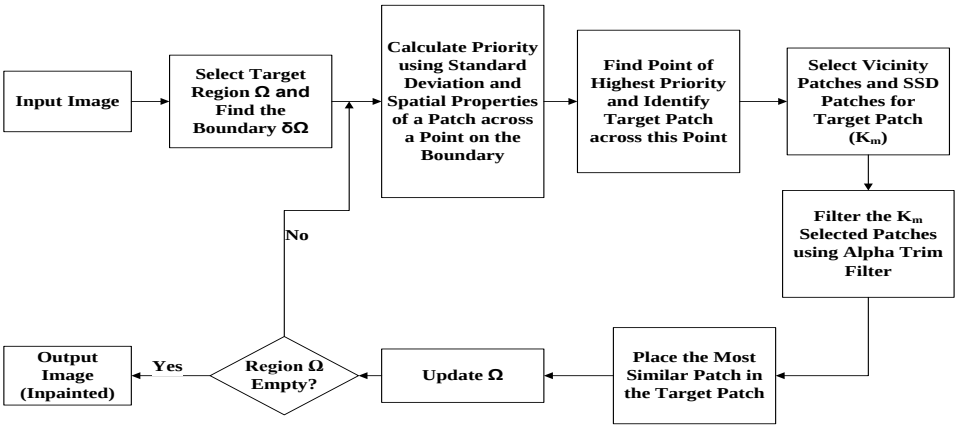

Fig 3: Flow Diagram of KNN-KV-Alpha Algorithm

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Flow Diagram of KNN-KV-Alpha Algorithm is shown in figure 3. The first step was to determine the region of interest. The next step was to determine the boundary between the known and unknown region. This boundary information was needed to fill the damaged pixels from the boundary towards the center. The priority value of each point on the boundary was determined using standard deviation of a patchwxw around each point and distance of the point from the center of the missing region.The priority term was evaluated for all the points on the boundary. The point on the boundary having highest priority was determined and a patch about this point was the target patch. The point on the boundary having highest priority was selected. A target patch of wxwacross this point was selected. The point of highest priority was at the center of this patch. This patch had some known pixels and some unknown pixels. $K_m$similar patches were found from the source region of the image which had similar pixel values as that of the known values of target patch. The metric used for selecting these patches was the sum squared distance between the known pixels of source patch and target patch. K_m patches also contain few vicinity patches. Out of the $K_m$patchesV_{n1} number of patches were the neighborhood patches where as K_{n2}were the nearest distance patches for each target patch, giving

$$K_m = V_{n1} + K_{n2} \quad (8)$$

K_{n2} patches were selected from the relevant segment using segmentation of input image with missing pixels.

These K_m multiple patches were filtered using alpha trimmed filter to obtain a single similar patch. The alpha-trimmed filter provided a better estimate than mean. Alpha trimmed mean was calculated by arranging the data in ascending order and summing the central part of the ordered array. The number of data values which were eliminated from the average was controlled by α trimming parameter which can be set between 0 and 0.5.This filtered patch was filled in the target region with center as the maximum priority point. The above steps 1 to 6 were repeated to reconstruct the entire missing region. These steps are illustrated in the flow diagram.

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 damaged 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 damaged pixels of target patch. This was achieved by varying row and column in all four directions excluding damaged part with the help of fill region F_g as mentioned in section 4.

Let(x_0, y_0) be the centre of target patch, (x_v, y_v) be the centre of vicinity patchand w be the parameter used to set patch width $(patchwidth = 2 * w + 1)$. The centers of all vicinity patches are obtained using equation 9, where$v$ is the patch width.

$$(x_v, y_v) = (x_0 \pm v, y_0 \pm v) \forall (x_v, y_v) \in \Phi \quad (9)$$

Hence the process will 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.

Group-Based Selection of Patches

The Kmeans segmentationwas implemented based on the center of group reference. For this algorithm implementation three segments were used. 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. The foreground and background belonged to two different groups. Any other object in the background was in the third group. K as three was good enough to search the patch from a related group. Too large value of K increased the overhead of the search algorithm. The main purpose of optimization of time was lost.

If the image was divided in Ksegments, then K reference centers were chosen, and initial classification of each pixel was made and labeled as per sum of square distances of each feature of the pixel from the reference as in equation11.

$$G = \{g \in \Phi : {}_{argmin} d(C_q, C_g) \forall C_q \in \Phi\} \quad (10)$$

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In the above equation $C_q$is the center of source patchΨ_q, $C_g$is the center of group g and$g \in 1,2\ldots.K$.Similar patches were selected from a group based on the point of highest priority. If this point belonged to a group then, similar patches (K_{n2}) from that group were selected by considering minimum distance between the known values of pixels in the target patch.

Patch Refinement using Alpha Trimmed Filter

The selected nearest K_m patches were arranged in order of neighborhood vicinity patchesV_{n1}followed by the K_{n2}nearest patches in ascending order of sum squared distance (SSD). The selected patches (P) were padded in extended columns as equation 12.

$$S = [P_1, P_2, P_3, \ldots\ldots P_{K_m}] \quad (11)$$

These K_m patches were filtered using alpha trimmed filter which was hybrid of the mean and median filters. The basic idea behind filter was for any array of elements the filter discarded the most typical elements and calculated average value using the rest of them. Alpha of the filter was indeed a parameter responsible for the number of trimmed elements.

The alpha trimmed filter filtered the selected patches with the nonlinear 'alpha mean' as the refined output. Of these K_m patches only one patch was obtained for pasting in the target patch. The refined value of the patch was given by equation.

$$I_p = \frac{1}{K_m - 2\alpha K_m} \sum_{j=\alpha K_m+1}^{K_m-\alpha K_m} P_j \quad (12)$$

For a given value α, the α-trimmed mean of the K_m patches in $S$was obtained by ignoring the αK_m smallest elements andthe αK_mlargest elements, and then computing the mean of theremaining elements.

The K_m source patches were chosen from source region based on the similaritybetween the known part of the target patch and the corresponding part of the source patches. The other part of each source patch corresponding to the unknown portion of the target patch was different from that of other source patches. For this reason, the α-trimmed mean filter was selected instead of a full sample mean or a fully truncated mean. When computing the intensity of a missing pixel using the corresponding pixels from the source patches, theα-trimmed mean filter was less sensitive extremelylarge or small intensity valuesthan the full sample mean. The α-trimmed mean filter provided a better approximation than the completely truncated mean. The filtered patch was then pasted at the target patch.

Algorithm 1: Proposed KNN-KV-Alpha 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. Determine boundary $\delta\Omega$, calculate$priority(p)$ using (1) for all points pin$\delta\Omega$.
3. Find point p with highest value of priority and a target patch around it.
4. Select multiple (V_{n1}) source vicinity patches by using equation 9.
5. Choose multiple (K_{n2}) SSD source patches from a group to which the target patch belongs to, using equation 10.
6. Filter multiple source patches $K_m = V_{n1} + K_{n2}$using alpha trimmed filter defined by equation 12 to obtain one refined patch.
7. Update the unknown pixels in target patch with known pixels in refined patch

II. KNN-SVD ALGORITHM

The priority value of each point on the boundary was determined using standard deviation of a patch around a point on the boundary and the distance of this point from the center. The point on the boundary having highest priority was selected and the target region was identified. Similar patches $K_n$were found from the source region of the image which had pixel values as that of the known values of target patch. The metric used for selecting these patches was the sum squared distance between the known pixels of source patch and target patch. Filter theK_n multiple patches using SVD to obtain a single similar patch. This filtered patch was filled in the target region with center as the maximum priority point.

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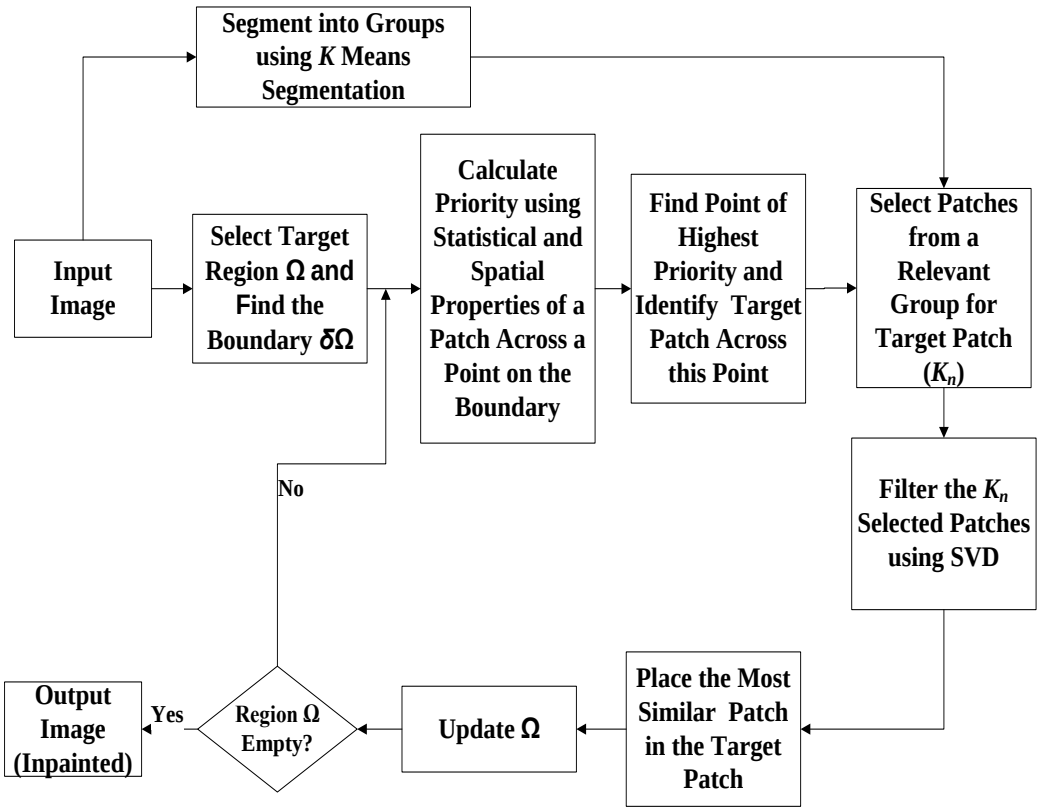

Fig 4: Data Flow Diagram for SVD Refinement of Patches

1. HOSVD 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 segmentationwas implemented based on the center of group reference. If the image was divided in K groups then Kreference centers were chosen and initial classification of each pixel wasmade, and labeled as per sum of square distance of each pixel from the reference as in equation (14).

$$G = \{g \in \Phi : {}_{argmin} d(C_q , C_g) \forall C_q \in \Phi\} \quad (13)$$

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.

$$Z = [P_1, P_2 , P_3 \ldots\ldots . P_{K_n}] \quad (14)$$

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 16.

$$a_i = T\{Z\}, \ where \ i = 1,2,3 \quad (15)$$

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

$$[U_i, S_i, V_i] = SVD(a_i), \quad where\ i = 1,2,3 \tag{16}$$

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 patchesselected 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 (18) and (20). The upper threshold t_2 was

$$t_2 = mean(S_i) \times r_2 \tag{17}$$

$$r_2 = max(\sigma_p), \ \forall\ P \in Z \tag{18}$$

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

$$t_1 = mean(S_i) \times r_1 \tag{19}$$

$$r_1 = min(\sigma_p), \ \forall\ P \in Z \tag{20}$$

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 thresholdt_1 and higher than the upper threshold t_2. Bandwidth of the filter wasr_2-r_1.

$$S_{f_i} = \begin{Bmatrix} S_i : t_1 < S_i < t_2 \\ 0, : otherwise \end{Bmatrix} \tag{21}$$

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

$$b_i = u_i S_{f_i} v'_i\ , \ where\ i = 1,2,3 \tag{22}$$

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.

$$A = \frac{\sum_{i=1}^{3} b_i}{3} \tag{23}$$

This refined patch to be pasted was obtained by using equation 24.

Algorithm 2: Proposed KNN-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. Determine boundary $\delta\Omega$, and calculate $priority(p)$ using equation (1) for all points pin $\delta\Omega$.
3. Locate point p with highest value of priority.
4. Find target patch around point p.
5. For each target patch$K_n$patches are selected from G to which the centre pixel $p$of the target patch belongs to.

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6. Filter K_n multiple similar patches using SVD to obtain one refined patch.

7. Update the unknown pixels in target patch with known pixels in refined patch.

2. Comparison of KNN-KV-Alpha Algorithm and KNN-SVD Algorithm with other Inpainting Algorithms

In this section performance parameters of KNN-KV-Alpha Algorithm and KNN-SVD Algorithm were compared with other existing algorithms for inpainting missing regions.The algorithms were written in MATLAB and executed on a system with processor: Intel i5 CPU@2.40GHz, memory (RAM): 4.00GB, and 64-bit operating System.

The images used for testing were acquired from Sony DSC-H300 with image width 5152, height 3864, bit depth 24, horizontal and vertical resolution of 350 dpi. Images from Berkeley Image Segmentation (BIS) dataset were also used for testing the algorithms. The images from this data set had image width 481, height 321, bit depth 24, horizontal and vertical resolution of 96 dpi.

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 parameters of two algorithms discussed in this paper were compared with Deng et al[12], Ding et al [11], Criminisi et al [3], KP[16,17],GRAD[18, 19, 20] algorithms and improvised data term algorithm (IDTA) discussed in paper[21].

The output images for various input images with inpainting domain identified are shown in figure 5. In the figure row-1 shows the original image, row-2 shows damaged 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.Quality factor for image-1 was46.08 for algorithm 1 and 45.84 for algorithm 2 and the time for inpainting is reduced by 46.97%. for image-2 the time for inpainting is reduced by 36.67%, for image-3 the time for inpainting is reduced by 29.98%. algorithm 1 took less time for inpainting because the similar source patches were found in the vicinity of damaged area.

The quality factor of KNN-KV-Alpha algorithm for image-1 was improved by 12.77% with respect to Deng algorithm. Time required for inpainting with KNN-KV-Alpha algorithm was reduced by 36.45% as compared with Criminisi algorithm for image 1. The output inpainted images were evaluated by taking peak signal to noise ratio (PSNR), structural similarity (SS) and time taken (T) for inpainting [22, 23]. The PSNR and SS though served the purpose of evaluation, few more parameters were defined to analyse the quality of an inpainted image. They were mean square error (MSE), cross correlation (XK), absolute difference (AD) and normalized absolute error (NAE) [24, 25].The quality factor Q used for assessment of inpainted images included all these factors.

Table 1: Performance Parameters of Proposed KNN-KV-SVD Algorithm for Image-1 to Image-3

Image-1 Performance Parameters of for a Damaged Area 1.2405%										
Algorithm	Q	SNR	SS	L	Q_{MSE}	XK	NAE	Q_{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
Image-2 Performance Parameters for a Damaged Area 1.1414%										
Algorithm	Q	SNR	SS	L	Q_{MSE}	XK	NAE	Q_{AD}	SC	T
Deng	36.21	36.93	0.9916	1	0.9999	0.9975	0.9983	0.9967	0.9962	30.82

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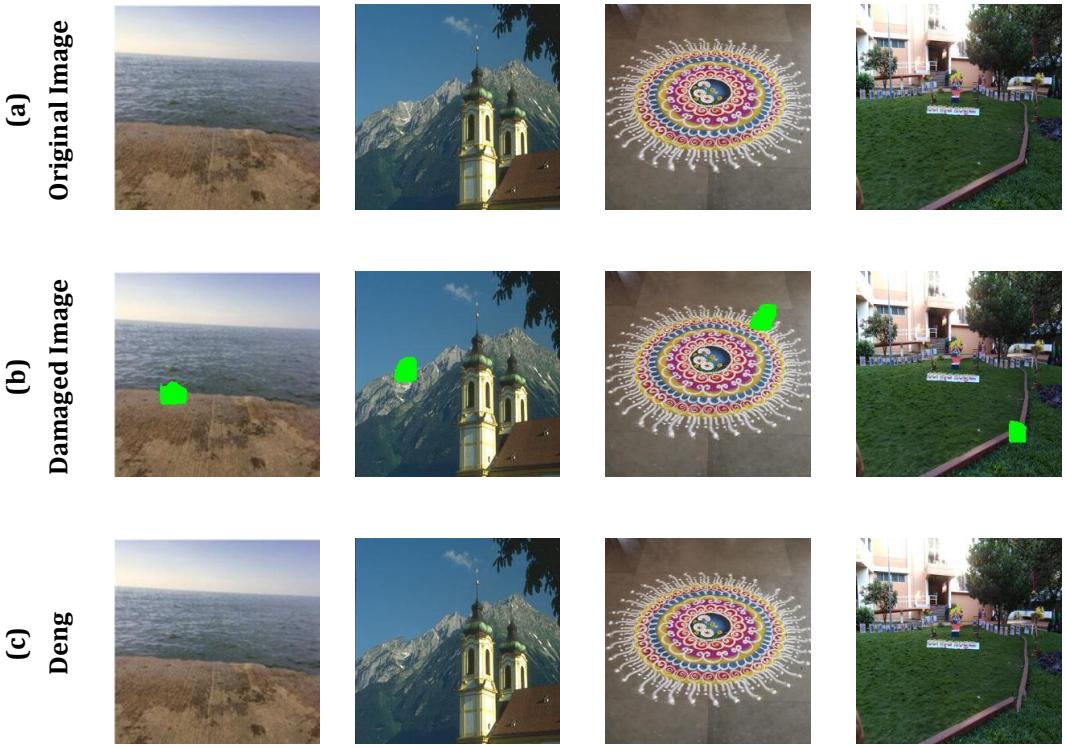
Ding	37.40	38.20	0.9914	1	0.9999	0.9972	0.9972	0.9980	0.9953	116.71
Criminisi	37.03	37.66	0.9931	1	0.9999	0.9977	0.9976	0.9984	0.9965	32.74
IDTA	36.06	36.78	0.9932	1	0.9999	0.9970	0.9971	0.9976	0.9953	32.96
GRAD	35.71	36.43	0.9931	1	0.9999	0.9970	0.9970	0.9977	0.9953	33.31
KP	36.73	37.42	0.9929	1	0.9999	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
Image-3 Performance Parameters for a Damaged Area 0.8484%										
Algorithm	***Q***	***SNR***	***SS***	***L***	Q_{MSE}	***XK***	***NAE***	Q_{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



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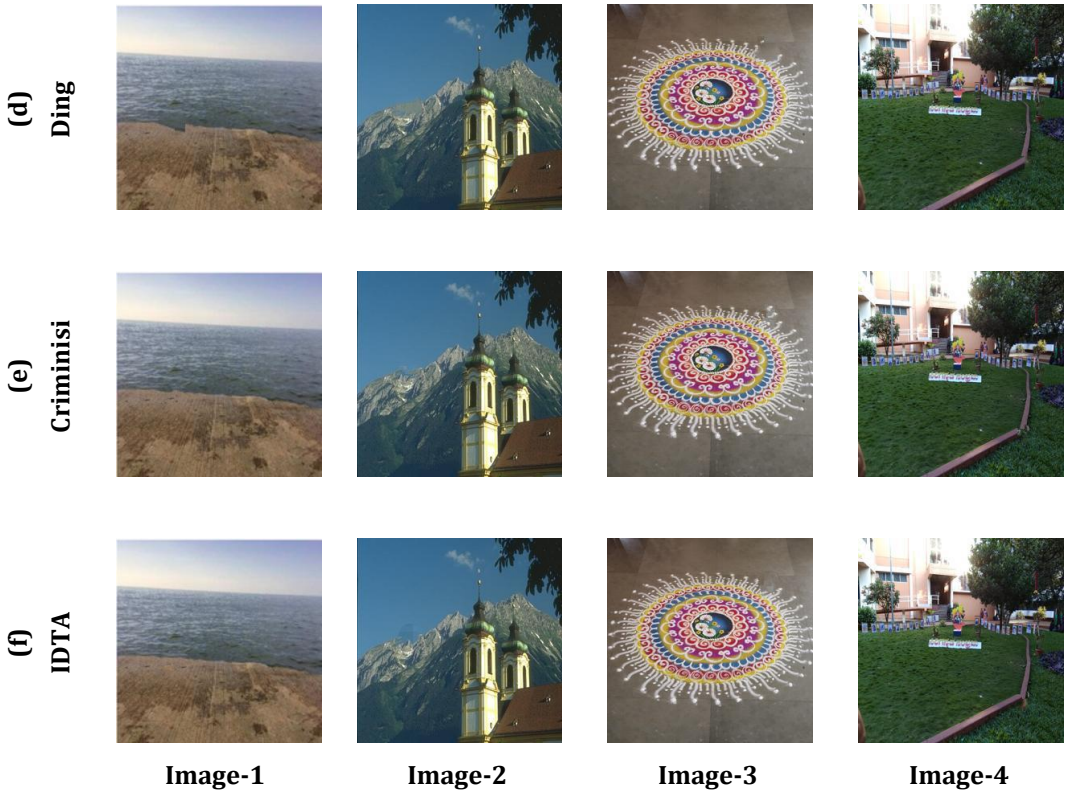
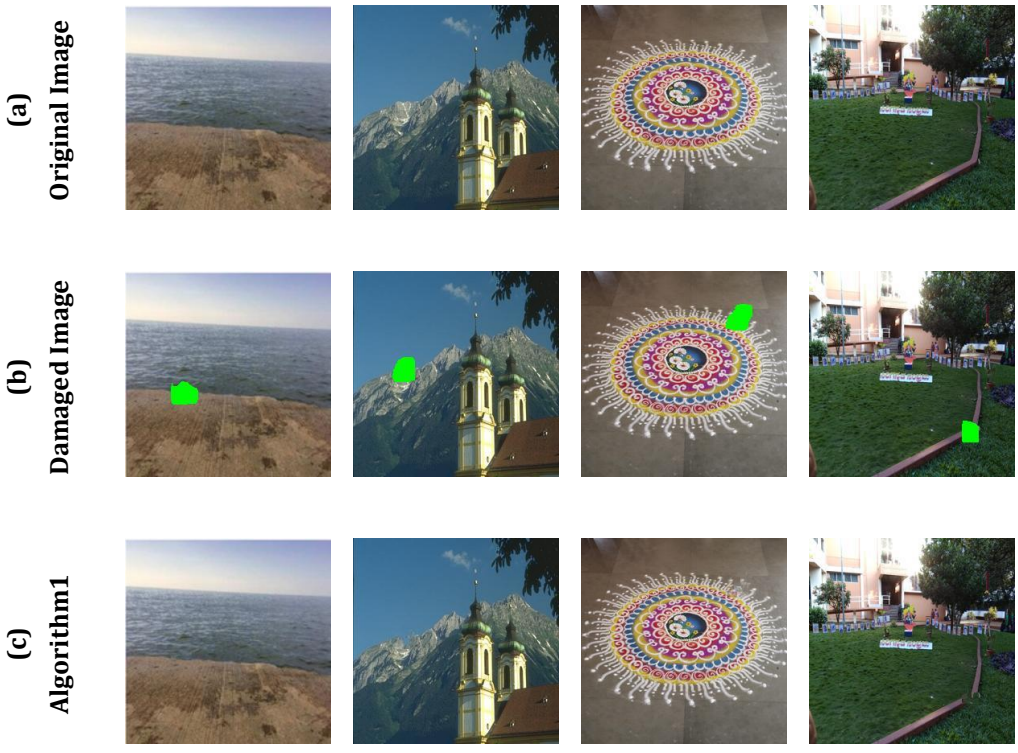


Fig 5: a) Original Image (b) Damaged Image Inpainting results— (c) Deng Algorithm (d)Ding Algorithm (e) Criminisi Algorithm (f) IDTA Algorithm

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



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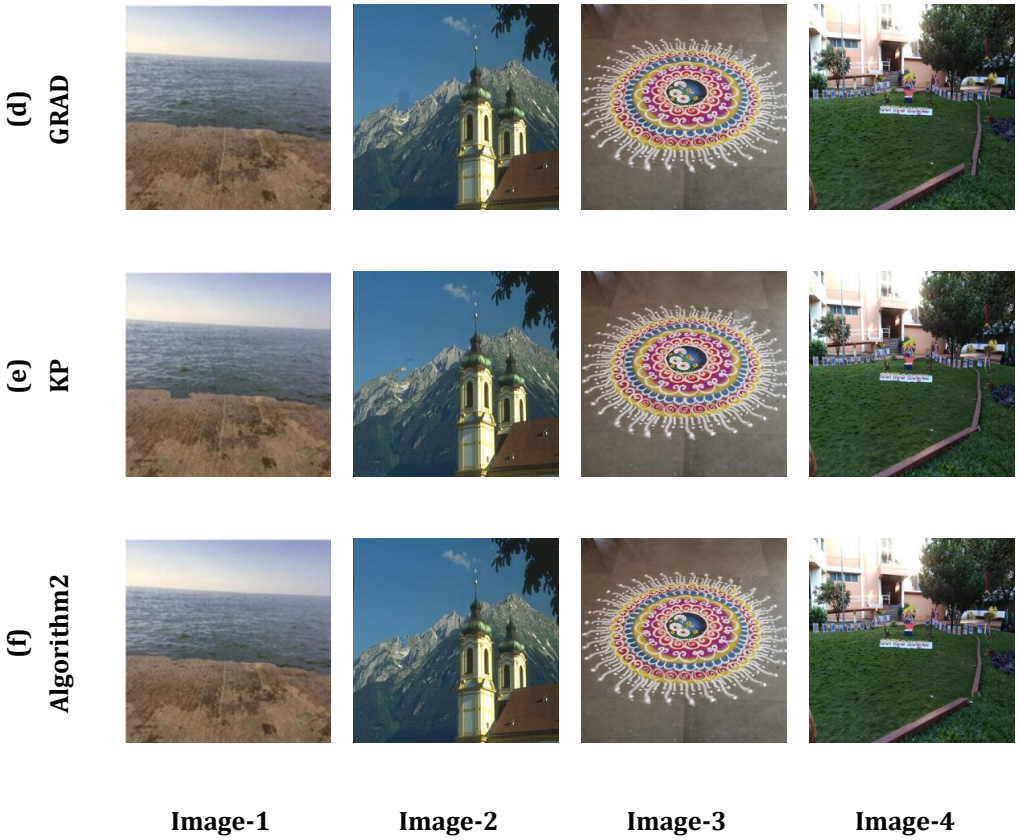

Fig 6: a) Original Image (b) Damaged Image Inpainting Results— (c) GRAD Algorithm (d) KP Algorithm(e) KNN-KV-Alpha(f)KNN-SVD

3. Results for 20 Images

The quality factor of inpainted images for Deng, Ding, Criminisi, GRAD, KP, IDTA, algorithm1, algorithm 2was tested for 20 images and the quality factor for these images is represented in table 2.

Table 2: Comparison of Quality Factor for 20 Images

Deng	Ding	Criminisi	GRAD	KP	IDTA	KNN-KV-Alpha	KNN-SVD
44.9307	40.8622	44.6198	43.7312	39.8843	43.804	46.0824	45.8353
36.2071	37.404	37.0273	35.7061	36.7316	36.0597	38.356	37.7687
42.2198	39.6271	44.5884	42.439	39.2386	42.8161	42.5052	42.4054
36.4813	36.0796	37.3588	37.5897	34.9974	37.8216	37.6784	37.4252
37.4099	43.0986	42.3591	37.6772	45.356	42.0124	40.0003	39.6371
37.976	38.6975	30.1848	32.4536	38.8645	33.9431	39.7488	39.4561
36.7698	36.5192	35.4259	37.5781	36.4694	37.6151	37.5625	37.1926
30.8668	32.0097	32.2209	31.4613	30.978	31.8324	33.3043	32.8881
24.2565	25.6643	21.328	25.6711	22.5732	24.2494	25.9773	25.4372
34.4615	35.2324	28.5128	36.1903	36.8068	34.4788	35.2777	35.0387
31.5088	32.9583	32.2329	31.304	33.7791	31.8443	33.6981	33.1766
35.7769	37.2581	38.6737	38.4267	37.4119	37.8817	38.2843	37.6965
42.3932	44.9392	43.8895	45.0733	43.6939	45.8139	45.8766	45.7336
34.5622	31.1125	34.2622	33.069	27.6519	32.0091	36.3784	35.7868

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24.7517	25.1536	26.8757	24.6791	24.2922	24.4058	28.0994	27.0838
24.1212	24.2914	25.3692	24.9813	26.3156	25.231	28.3347	26.7133
22.654	21.3402	23.1212	21.4854	24.1559	21.4274	26.3158	24.7518
31.1327	31.6319	32.6076	32.0856	31.7133	31.419	36.6207	36.1267
27.7237	30.1251	29.7252	29.671	30.4075	32.0844	32.6134	31.7645
24.3517	25.4536	26.9057	24.3058	24.6391	24.2882	28.5547	27.3038

The quality factor tabulated in table 2 are plotted in figure 7 with x-axis indicating image number and y-axis indicating quality factor. Figure 7 shows that the quality factor of KNN-KV-SVD algorithm was reasonable than all other algorithms for most of the images.

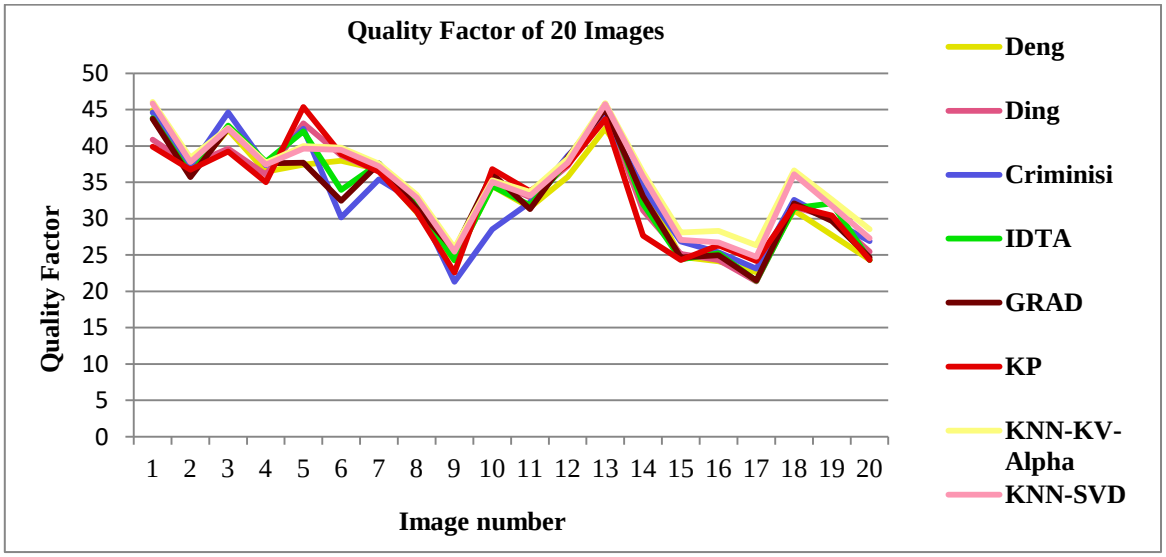

Fig 7: Comparison of Quality Factor for 20 Images

III. CONCLUSION

The KNN-KV-Alpha algorithm and KNN-SVD algorithm were implemented in MATLAB. The algorithms used for comparison IDTA, KP, GRAD, Deng and Criminisi were also simulated in MATLAB. The results were obtained by executing the algorithms on the same system with same input image, area and position of missing pixels. The performance parameters Q, PSNR and T facilitated analysis of the results. For most of images proposed KNN-KV-Alpha performed satisfactorily and in comparison, with the other algorithms. The results showed that KNN-KV-Alpha reconstructed the missing area faster with high quality factor for most of the input images.

In this paper the priority was calculated based on standard deviation of the patch around a point on the boundary between the known and the unknown region along with distance of the point from the centre. Vicinity patches and SSD patches were selected and refined using alpha trimmed filter. Performance parameters were analysed for reconstruction of missing pixels and object removal. Results showed that priority calculations of this kind worked satisfactorily than other standard algorithms. This work also suggested the search of source patch from a segment and selection of vicinity patches which reduced the time for the process of inpainting. Further alpha trimmed filter provided the most similar source patch to be filled in the target region and retained the prominent pixel values in the patch. Segmentation of pixels based on K means saved significant time and improved the speed of reconstruction.

The KNN-SVD algorithm was tested for a variety of images and improved the visual quality of reconstructed image. In some images the quality factor was high, but the visual quality was low and vice versa. Since the singular matrix was huge in size the lower values near zero were eliminated for enhanced reconstruction. The KNN-SVD algorithm used segmentation-based patch selection for selecting multiple source patches which were refined using SVD. The threshold values for SVD algorithm decided the bandwidth of the filter. Higher values of SVD indicated sharp edges and lower values indicated smooth regions. The sharp edges were retained, and

smooth regions were removed to obtain the resultant target patch. KNN-KV-Alpha showed improved performance as compared to KNN-SVD. When compared with other standard algorithms these algorithms performed satisfactorily.

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