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Research Article

Inpainting with Refinement of Vicinity Patches using alpha trim filter for Heritage Sites

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Abstract

Image processing and computer vision have been active areas of research and used in different applications. Few researchers have attempted the use of image processing techniques in the digital preservation of heritage sites. Heritage sites across the world are important sources of knowledge which introduce us to our cultural history, depicting the evolution of humankind. Digital reconstruction of ruined historic monuments and heritage sites can help in visualizing how these may have existed in the past. Also, such a process requires no physical alteration to the existing monuments. Inpainting is the process of restoring image contents imperceptibly. The contribution of this paper is patch based inpainting technique with standard deviation used as a parameter to find the pixel of highest priority. In the search strategy v vicinity patches in the neighborhood of the destination patch with center pixel of v belonging to the boundary of destination patch is used. The vicinity patches are searched merely by looking at the known and unknown pixels of the destination patch. Experimental results carried on a set of 90 images in comparison with standard techniques show improved performance.

Keywords: *Inpainting, Image Reconstruction, Heritage Sites, Exemplar Based Inpainting, PSNR, SSIM, Quality Factor, Vicinity Patches.*

1. Introduction

Innovation in architecture is important, but preserving and restoring the historical monuments is also important because they reflect our history, and help us to understand and respect people who lived in different eras with different habits and traditions. These old monuments help us to study the changes in the societies and the reasons that lead to the development of cities, societies and traditions. To preserve the heritage sites physical renovation can be done. Renovation may not only pose danger to the undamaged monuments, but may also fail to mimic the skillful historic work. On the other hand, it would be interesting to digitally reconstruct the heritage sites while such a process avoids physical contact to the monuments. The digitally reconstructed heritage site serves as a source for entertainment and study. In today's world, preservation of the digitally reconstructed monuments is inexpensive with the availability of better computing and storage facilities. Inpainting is the process of restoring the image contents imperceptibly. Given an image and a region of interest (ROI) in it, the task of an inpainting process is to fill the pixels in this region, in such a way that either the original content is restored or the region is visually plausible in the context of the image. Inpainting can be used for a number of applications that require automatic restoration or retouching of some region of an image. The term inpainting is derived from the art of restoring damaged images in museums by professional restorers. Pixels in the missing region (i.e. the ROI) can be filled either by gradually propagating information from outside the boundary of the ROI or by making use of cues from similar patches. Based on these filling strategies, the existing inpainting methods can be categorized into two important groups viz. (a) methods using level lines and solving partial differential equations (PDEs) and (b) exemplar based techniques. Exemplar based methods are more popular as they can fill larger damaged regions with good results. As inpainting is an image editing tool the regions to be inpainted are required to be manually selected by the users.

Image inpainting (C Guillemot, *et al* (2014)) PDE methods are classified as linear, nonlinear, isotropic, or anisotropic to favour the propagation in particular directions or to take into account the curvature of the structure present in a local neighbourhood. These methods perform good for straight lines, curves, and for inpainting small regions. They are not suited for

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recovering the texture of large areas, which they tend to blur. The second category of methods is based on the statistical and self similarity priors. The statistics of image textures are assumed to be stationary or homogeneous. The basic idea in (A. Criminisi *et al* 2004) is of exemplar- or patch-based methods is to fill the target region by copying the well-matched source patches (i.e., candidate patches from the source region) to the corresponding target locations. These methods perform efficiently for removing large objects from digital photographs. The simultaneous propagation of texture and structure information is achieved by a single, efficient algorithm. The flow of the algorithm is based on a priority term which is defined using confidence term and data term.

The exemplar (Fan Qian *et al* 2015), based technique is improved by using adaptive size of window; the size of window is selected based on patch sparsity. Three similar patches are selected and difference between them is calculated. If the difference is less than a threshold, it means that the location of these patches is nearly the same place, so it selects the most similar patch to inpaint. If one of the differences is larger than a threshold, then it expands the patch size and selects the correct patch. Another algorithm (Olivier Le Meur *et al* 2011) relies on the use of structure tensors to define the filling order priority and template matching. The structure tensors are computed in a hierarchic manner whereas the template matching is based on a K-nearest neighbor algorithm. The value K is adaptively set in function of the local texture information. Paper (R. Martinez *et al* 2015) suggested improvement in the fill-in order based on a combination of priority terms, previously defined by Criminisi, which encourages the early synthesis of linear structures. The second contribution is modification in distance calculation for selecting a similar patch by using Hellinger distance. The structure tensor is used to construct a structure control function to depict the image block information. Adding the structure control function into the priority formula to increase the structural information effect and ensure appropriate transmission of the structure information and thus reduces the error matching rate. A matching (LIU Ying et al)relation which decreases the number of calculation for the distance measure, and reduces the time complexity by converting the global search matching algorithm into local one. An improved method (Kaushik kumar et al) in which image inpaint is performed accurately by modified distance function using image gradient as a similarity metric.

Structure sparsity (Zongben Xu et al) was designed by measure of the sparseness of the patch similarities in the local neighborhood. Higher priority is given to patch with larger structure sparsity, which is generally located at the structure, and is selected for further inpainting. The patch sparse representation is used to synthesize the selected patch by the sparsest linear combination of candidate patches under the local consistency constraint. A (Wun-Hua Rd *et al* 2010) patch-based image inpainting is based on structure consistency and variance between the adjacent points in the target region. (Song Zhang *et al* 2011) Criminisi's algorithmic performance is enhanced by using variable patch size and confidence value to be updated of the newly inpainted patch dependent on current searching accuracy.

2. Proposed Algorithm

The monuments of each era have their own style and structural distinction that helps archeologists in predicting the age of the monuments. From the earlier era till eighteenth century the historical monuments developed from being rectangular to doom structured tops to finite details in added in the form of fine arts. The focus of this work is to exploit the statistical properties of foreground and background to detect the continuity or discontinuity of certain structure and reconstruct the damaged parts by taking into account that the structure is an extension of what is remained from the damaged portion keeping in mind the similarity of pixels values.

Our main contributions are

(i) A new method to determine the Filling Priorities based on statistical and spatial properties.

(ii) Grouping of pixels of image based on K means clustering and hence a group-based patch selection method to find the candidate patch from a restricted and minimized search space.

(iii) A neighborhood patch search method based on the location and continuity of the image structure about destination patch in addition to the SSD found patches which are to be refined alpha trim filtering by joint filtering of multiple patches to capture their pattern for restoration.

2.1. The Priority term and its significance

The priority term is an array of value based on certain criterion that decides which of the patches around the damage is the most suitable one to be filled first so that the method proposed results give out better quality for in painting.

There is always a user intervention as image inpainting is an image editing tool. Since the patch being chosen is a square one, it is quite a possibility that next suitable patch centre lies on the straight line forming the square being filled during earlier iteration, in the case where the priority is chosen based on the number of pixels known in the destination patch. Also for the next cycle higher priority will be given to the patch that lies on the straight line of at least w (patch width/height) pixels giving higher known pixels than unknown pixels. Hence the patch fill order follows the previous filled patches proceeding and filling the interior of the damaged region, moving towards filling some of the borders which is not feasible in cases where image structure is to be restored.

To solve this problem 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. This works fine when the damage and its cover chosen by the user are circular. When the damaged region is of irregular (specifically non-circular) shape as is the case most of the times in nature, it fails to restore the details of the elongated axis of the damage. For example a damage of near elliptical shape will be filled details around shorter side, leaving out details connecting longer one. An argument could be put forth to alleviate this problem by choosing the circular cover manually to allow the filling converge to the centre. However that adds to two disadvantages, first the circle will be too big and we are labeling and throwing too many known pixels in to unknown region purposefully. Second disadvantage is that it will automatically add to the execution time by many folds. Inclusion of the data term structure tensor into the priority term improved the results, still applicability of this method to the present topic was found limited.

In this work the priority of the patch to fill is decided based on the standard deviation of the patch around destination pixel 'p'. A higher value of the standard deviation implies that the destination patch is on the edge belonging to the different groups in this case foreground and background as well as high variation of pixel values, whereas a lower value would mean it belongs to only one group or the all pixels are similar. In terms of k means the patch with higher value of standard deviation contains the pixels belonging to multiple groups as compared to lower deviation ones. We take the inverse of deviation as part of priority term hence the filling of the patch begins with either foreground or the background pixels of the damaged region. However in case of the irregular shapes/damages to be filled, the destination of the target from the center of the damage region is added into the priority term making the far ends of longer section of the damage a higher priority. The new fill order will be decided by the combination of the standard deviation of destination patch and its distance from centre of damage. The priority term is

$$\mathrm{priority(p)} = \mathrm{norm}\left(\frac{1}{\mathrm{std(p)}}\right) + \mathrm{norm(d)} \qquad (1)$$

$$\mathrm{d} = ((\mathrm{y(p)} - \mathrm{yr})^2 + (\mathrm{x(p)} - \mathrm{xc})^2)^{1/2} \qquad (2)$$

p =is the central pixel of the destination patch,yr=central row of the damage area, xc=central column of the damaged area, std= standard deviation of the destination patch around p, norm is normalization operator.

The standard deviation of patch is calculated by considering all the pixels of patch in case. Here the unknown region pixels considered which play vital role in deciding the value of standard deviation, based on number of pixels unknown the deviation will vary for the same components and composition of known part of patch. Hence in a manner even though the number of known pixels is not directly included in priority value, it still plays a role in contributing to standard deviation Figure 1 shows an image with a damaged portion which is closed by more than hundred boundary pixels as seen on the x axis components of figure1 (b). The priority for each of these points/pixels as calculated by using equation (1) is displayed as the y axis component of the figure 1(b). The combined highest priority is awarded to the pixel number 10 of the figure 1(b), which is associated with the pixel located at 224th row and 81th column of the image input, implying that the first patch filled will be the one around this pixel with chosen width w.

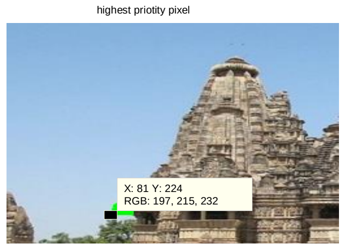

Fig 1(a) highest priority pixel

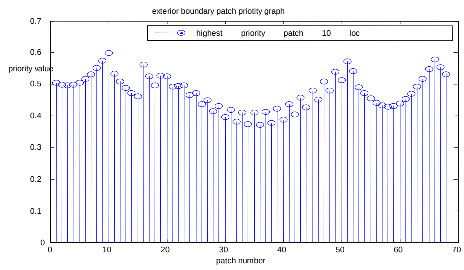

Fig 1(b) priority graph

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, it is observed in as depicted in fig(2), 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, not considering the property of pixels in the neighborhood, resulting in more noise in restored image. Therefore the inverse of deviation is taken to start the filling from either from the interior of the foreground or exterior of the background and proceed towards centre of damage. The distance term in the priority ensures that filling of lower deviation (similar) patches is limited to a few in a row, choosing patches that are extreme from centre of damage in between. The border pixels between two different groups (fore and backgrounds) and centre of damage are one of the last to be filled, giving better results than standard deviation only as priority term.

2.2. Image segmentation and patch selection

A patch from the source region is selected based on minimum distance in each of its constituent components from the destination patch. In this work a total of K patches are being selected. These K patches are to be refined based on alpha trimmed mean filter which enables multiple feature inputs to be filtered to select of prominent varying features as output. Of the K patches Vn number of patches are the neighborhood patches where as Kn are the nearest distance patches for each destination patch, giving K=Vn+Kn. Since the Kn will be greater than one, it will add to number of searches and hence add to the execution time. To counter this effect we divide the total search space by using k-means segmentation and limit space for a matching patch to the pixels of specific segment only. Now the search area is limited to the segment to which the centre pixel p of the destination patch belongs to and as a result the source area under search for suitable patches and hence time required is reduced significantly, especially in the images where variation is large.

2.3. Vicinity patches

It is not guaranteed that the nearest two patches to destination are the patches in the immediate vicinity to it. Hence even though the search area is limited by a big patch locality, chances are that one may miss the patches in the most vicinity. The vicinity patches are searched merely by looking at the known and unknown pixels of the destination patch. Since the centre of the destination patch is at the boundary between damaged and undamaged or unknown and known pixels or the destination and source regions respectively. A square patch with size wxw will have at least one of its corner patch covered under damage region. The vicinity patches are selected from the source pixels which are part of the destination patch and as a thumb rule all the pixels of vicinity patches belong to the source region. The centre of the vicinity pixel lies on the border pixels of the destination patch. Therefore minimum of one and maximum of three vicinity pixels can be extracted from the source. These vicinity patches lie on the diagonally opposite side to the damaged pixels of destination patch.

Hence the process will form to be the continuation of the structure that is opposite to the missing part of pixels in combination to the nearest distance pixels.

The k means clustering is implemented based on the center of group reference. Let us say image is to be divided in k groups then k reference centers are chosen and initial classification of each pixel is made, and labeled as per sum of square distance of each feature of the pixel from the reference as in equation(3).

G(i,j)=g:{argmin(ssd(I_(i,j),C_g)) } (3)

Where Cg=centre of group g; g∈1,2..k

I= the input image

The selected nearest K patches are arranged in order of neighborhood vicinity patches followed by the kn nearest patched in ascending distance padded in extended columns

$X = [p_1, p_2.p_{vn}, p_{k1}, p_{k2}, \ldots p_{kn}]$ (4)

Here the depth is n=3 for color images, RGB. However the nonlinear filtering is implemented by alpha trimming for all these channels taking one at a time.

The alpha trimmed filter selects only a few of the selected patches and finds the nonlinear 'alpha mean' from those as the refined output.

Equation (4) can be treated as a single array of K patches

$S_K = \{X1, X2 \cdots XK\}$ (5)

Of these K only a few are to be selected the lower and upper patch number are selected from by the 'α' value. The refined value of the patch is given by equation (6)

$Ip\ (l) = \text{mean}\alpha(SK) = 1/(K - 2\alpha K) \sum_{j=\alpha K+1}^{K-\alpha K} Xj$ (6)

The filtered patch is then pasted at the destination patch.

3. Simulation and Result Analysis

3.1. Performance parameters for inpainted image

The quality reconstruction of an image is measured by various parameters based on the application of interest. For inpainting PSNR is one of the most important parameter when the damage is at the foreground of the monuments while the structural similarity (SS) plays role when the damaged area covers edge structures of the monuments. The PSNR and structural similarity though serve the purpose broadly there are few more parameters which are important in deciding the quality of an image such as mean square error (MSE), luminance(L), cross correlation(XK), absolute difference (AD), normalized absolute error (NAE) and structural content(SC)[19]. The error measures AD, NAE, MSE result in lower value for cases of better reconstruction, where as rest of parameters give a higher value for better results. To quantify the quality as single term using all the parameters, the error parameters are complemented by subtracting from the maximum possible error value and normalized down. The quality of reconstructed image is given by Quality factor' Q' which is defined as the product of all modified quality measure parameters.

Q= PSNR*SS* MSE*XK*NAE*AD*SC*L (7)

While measuring error or difference the maximum possible error value depends on the p_m maximum value the pixel can be given based on the format (8 bit or 16 bit unsigned) subtracted minimum value pixel can take, which is 0. Final error depends on the number of pixels in the image; therefore maximum possible error is defined in general as

$MPE = \sum_i \sum_j p_m \ ; \forall\ i, j$ (8)

An error E between two images X and Y is defined by

$$E_{i,j} = (x_{i,j} - y_{i,j}); \{\forall\ i,j\} \tag{9}$$

Modified mean square error defined by

$$MSE = \sqrt{\sum_i \sum_j (MPE - E_{i,j})}\ /MPE; \{\forall\ i,j\} \tag{10}$$

Letter L stands for the variance of image luminance, equation of the luminance function for two images, L(x,y) is:

$$L(x,y) = \frac{2u_x u_y + c1}{u_x^2 + u_y^2 + c1} \tag{11}$$

μ_x and μ_y separately represent the mean value of the images x, y, reflecting the luminance information. $C1$ is a positive number close to zero, which is brought in to avoid the case that denominator equates zero. NAE is the normalized absolute error given by

$$NAE = \frac{\sum_i \sum_j (MPE - |E_{i,j}|)}{MPE}; \{\forall\ i,j\}i,j \tag{12}$$

AD is again an error measure stands for average difference, again this value may reach zero in ideal case of reconstruction hence modified to

$$AD = \left(\frac{\sum_i \sum_j (|MPE - E_{i,j}|)}{MPE}\right); \{\forall\ i,j\} \tag{13}$$

In all the cases MPE is image and case specific, it will have different value for same size of row column with different dimensional images.

4. Result and Observations

Some of the results of proposed method are compared with EBIIMPD (Deng L-J *et al* 2015), alpha trimmed filter (Ding Ding *et al* 2019), Criminisi algorithm (Criminisi *et al* 2004), Tensor algorithm (Olivier Le Meur 2011) methods, by creating damages of various shape and size at different spatial locations in the image.

The lower and upper cut of ranges affect the selection of patches, since we are interested more in details and sharp edges the parameter alpha is selected to be 0.2, a value α=0 is a linear mean or average of the K patches, where as maximum value that can be given to α should be less than 0.5 theoretically. Hence a lower value of α add in smoothness, too smooth values tend to induce errors, therefore a substantial lower cut of is necessary to eliminate the smooth values. The results are shown in figure 2 to 5 for EBIIMPD (Deng L-J *et al* 2015), alpha trimmed filter (Ding Ding *et al* 2019), Criminisi algorithm (Criminisi *et al* 2004), Tensor algorithm (Olivier Le Meur 2011) and proposed method(P). Table 1 depicts the performance parameter Q for Image 1 to Image 4. It can be seen that the proposed method performs better in the cases where there is an edge as well as texture to be recovered. The cases of failure are also added in these chosen damages where other methods like criminisi and tensor based perform better than proposed methods.

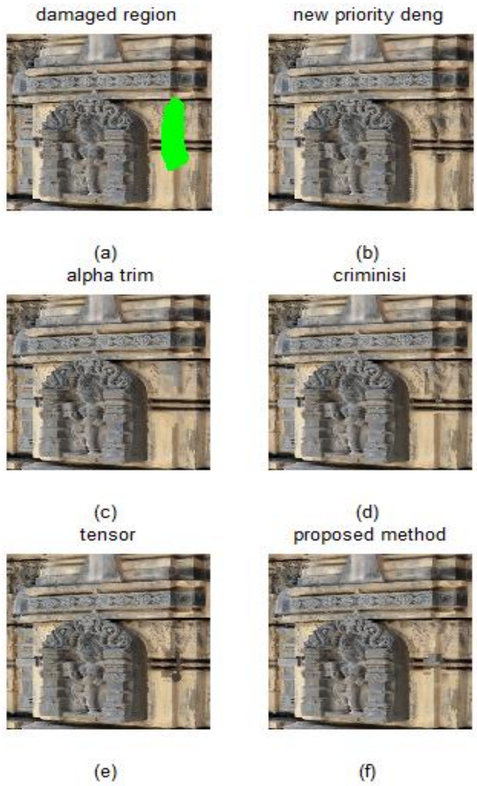

Fig 2 a) Damaged region, (b) EBIIMPD [18] (c) Alpha trimmed filter (d)Criminisi Algorithm (e)Tensor, Algorithm (f)Proposed method

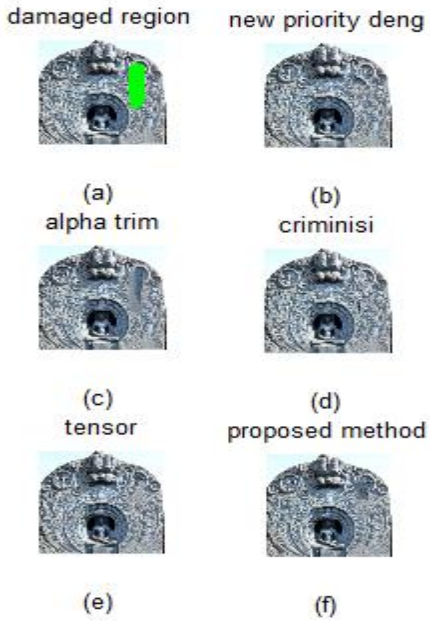

Fig 3 a) Damaged region, (b) EBIIMPD (c) Alpha trimmed filter (d)Criminisi Algorithm (e)Tensor, Algorithm (f)Proposed method

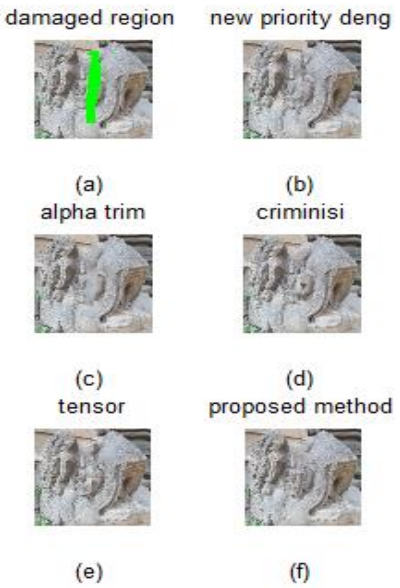

Fig4 a) Damaged region, (b) EBIIMPD [18] (c) Alpha trimmed filter (d)Criminisi Algorithm (e)Tensor, Algorithm (f)Proposed method

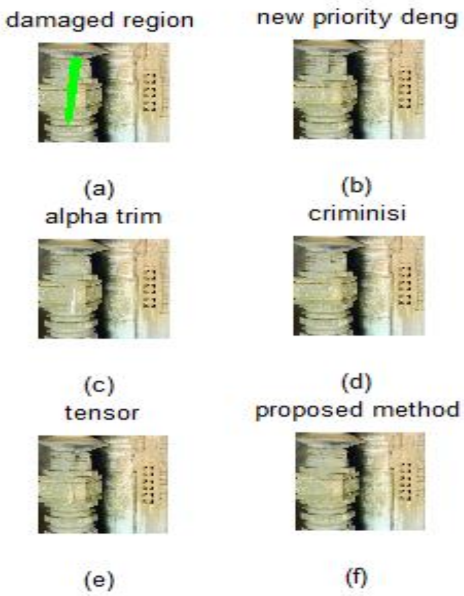

Fig 5 a) Damaged region, (b) EBIIMPD (c) Alpha trimmed filter (d)Criminisi Algorithm (e)Tensor, Algorithm (f)Proposed method

Table 1 Performance parameters for image1 - 4.

Method	Image1	Image 2	Image 3	Image 4
Area %	0.9704	2.3315	1.444	1.6756
EBIIMPD	37.53	34.11	30.73	36.83
Alpha trim	30.86	35.71	32.33	39.22
Criminisi	36.16	37.19	32.31	37.77
Tensor	35.11	36.99	33.23	39.92
Proposed	40.17	39.52	34.45	40.21

The width of the patch to be considered is of significance, since for capturing details damaged under a small region, a small size is necessary and for larger damage smaller patch size is tax on execution time. Table 2 is a typical example of different images with random damages.

Table 2 Performance quality with different patch widths for 3 different images

Image	% Area damage	Quality Q factor		
		W=5x5	W=15x15	W=21x21
1	1.3916	30.13	37.90	37.57
2	1.3077	32.89	41.79	41.06
3	0.7919	36.94	38.13	40.05

The mean standard deviation of the patches around the damage for these images is 0.0226, 0.0124 and 0.0521 respectively. This implies that the reconstruction is better with larger patch size for consistent texture around damage region. As the deviation increases a smaller patch size is preferred.

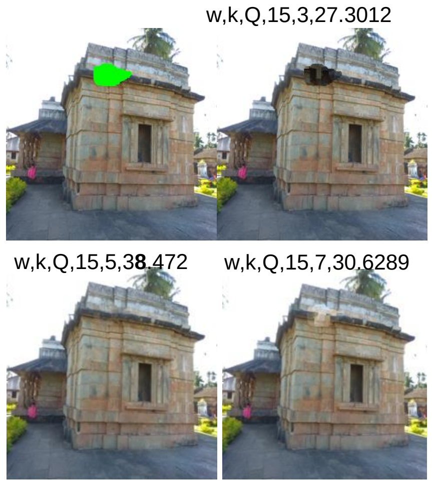

Fig .6. Damaged Image 1 Reconstruction of image 1 with K= 3,5,7 patches of 15x15 pixels

The method 'vicinity and nearest patches based inpainting' is based on the presumption that there are multiple (K), patches. It is known that there could be at max 3 vicinity patches and the rest of the K patches are to be found by nearest distance patch search exemplar method. The criterion to limit the number of patches is both user's choice as well as time dependent because every patch search needs iteration through the source segment. However increasing number of patches does not guarantee better quality. When the patch has large deviation, the vicinity patches add more to noise than improving the quality. Whereas when the damage is spread in plain area with almost no standard deviation among the constituent patches then the criminisi method offers better quality. In addition to the above observation it is found that for the damage of circular or more of spread area the performance of the proposed method is found not being suitable. Performance parameters Q are tabulated in table3 for number of patches taken to be 3, 5 and 7 for three different images. The figure 6 shows the reconstructed versions with 3, 5, 7 patches of size 15x15 pixels. It can be seen that the more nearest distance patches or only the vicinity patches have on an average worse quality of reconstruction hence the Kn SSD determined patches are integral to the better performance of this technique. Also it is seen from table 1 that in the special cases as defined by objective of this paper, the proposed method performs better than the standard alpha trim filtering of K nearest distance feature patches.

Table 3 Performance quality varying number of patches K for 3 different images with patch size 15x15

Image	% Area damage	Quality Q factor		
		K=3	K=5	K=7
1	1.3916	27.30	38.47	30.63
2	1.3077	27.72	41.71	34.18
3	0.7919	34.16	38.13	38.46

For the damage which has very small coverage percent area smaller size of patch give better match, where as for input image with larger damage area the larger patch size gives better results. However too big a patch results into errors and hence lower PSNR, and a too small patch size over writes the pixels and results in errors, hence an optimum width is subject to the damage area size. To avoid confusion the input image size is fixed to 256x256 pixels, the optimum patch size is dependent on the percentage area covered by the damage region. Table 4 shows that alpha as 0.2 gives better results. Table 5 shows that the proposed method needs less time and gives good quality factor as compared to EBIIMPD (c) Alpha trimmed filter.

Table 4 Performance quality with varying alpha for an image with patch size 9x9 with k=5.

Elapsed time	Q	alpV	area
164.03sec	25.29	0	5.7663
133.49 sec	25.34	0.1	5.7663
118.15 sec	27.10	0.2	5.7663
119.76 sec	27.83	0.3	5.7663
199.17 sec	27.96	0.4	5.7663

Table 5 Quality factor and time comparison

Method	Elapsed time	Q	Q_by_T	area
Proposed	94.6881	31.14	0.3289	3.9017
EBIIMPD	182.7558	29.45	0.1612	3.9017
Alpha trim	872.8801	30.04	0.0344	3.9017

4.1. Effect of segmentation

Segmentation is mainly benefits in reducing the time required for search for patch execution,. The image is divided in 3 segments for experimental purpose, for an ideal image total number of pixels are equally divided in the k segments, hence the time taken by using k means segmentation would have be a third of that taken in case of sequential image search throughout the image. However in practical case is not so. It is highly possible that one segment of image may have more pixels in t than other two classes; some of the example outcomes depicted in figures 10, 11 and 12. The three different input images considered here with damage area region covering 1.4%, 1.3% and 0.79% respectively. As the area of damages region is direct pointer to time required to fill it, so is the width of the patch. The larger the width lesser the time required for filling up the region. Figure 10 shows the time taken for filling the damage region for both images with and without segmentation along with the widths of the patches chosen for doing so. It is clear that time taken to execute a program is better in cases of segmentations. It can be observed that time taken for each case image is almost halved due segmentation compared to that of without segmentation. As the patch widths is increased from 15x15 to 21x21 the time is reduced to almost by a third, which augurs well with the arithmetic. Another observation is that the larger area of damaged region takes longer than the smaller region, which indicates that the number of searches has more impact on time optimization than the reduction in source region if and when the damaged region is increased.

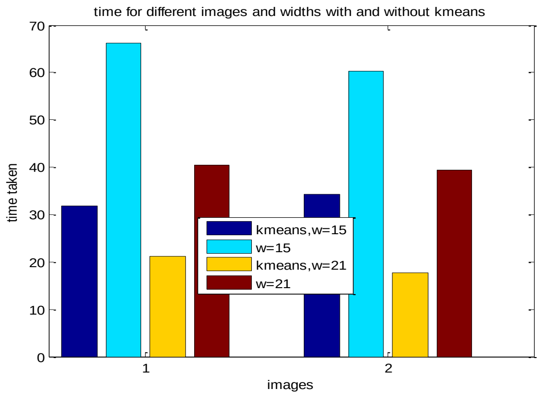

Fig.10. Time optimization for segmentation K=5

The segmentation even though limits the source area for searching a patch that matches the destination; in general it affects the quality of image reconstruction. The quality outcomes for fixed patch size for the same three case images are as shown in figure 11.

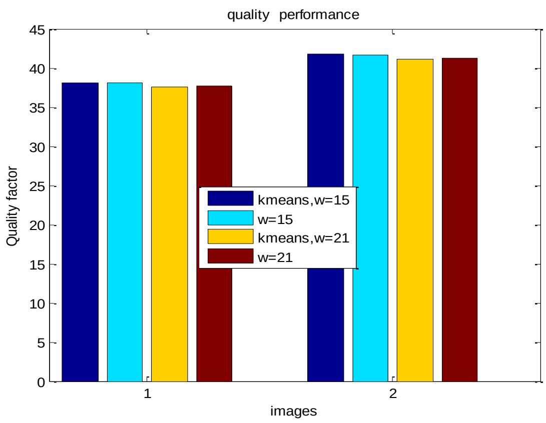

Fig.11. Quality factor for segmentation K=5

The quality of image in few cases without segments is slightly better than the segmentation case. That is the compromise that can be made as we can see that the total impact of quality and time is better in case of segmentation as depicted in figure12. Figure 13 and 14 depicts the performance parameter Q for a data set of 5 and 100 images. The proposed method performs better than the other methods.

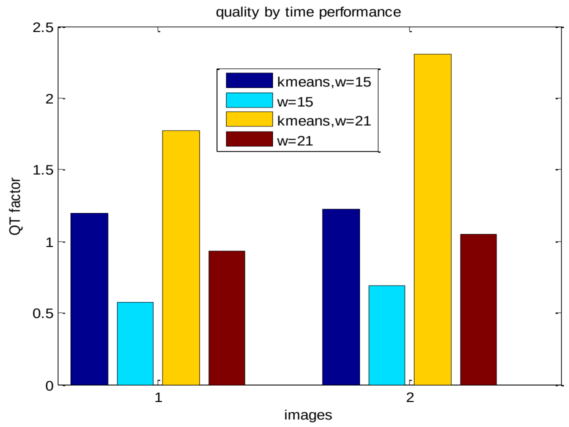

Fig.12. Quality /Time comparison for segmentation

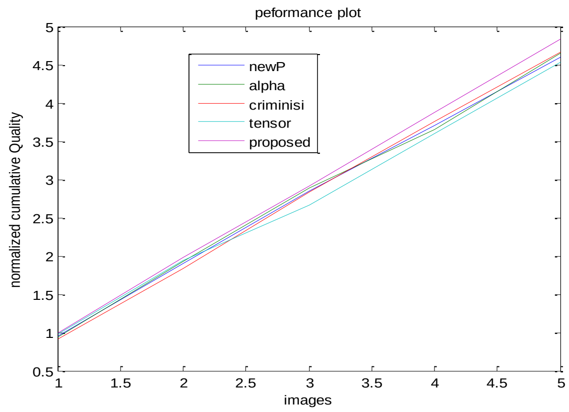

Fig13 Quality plot for a data set of 5

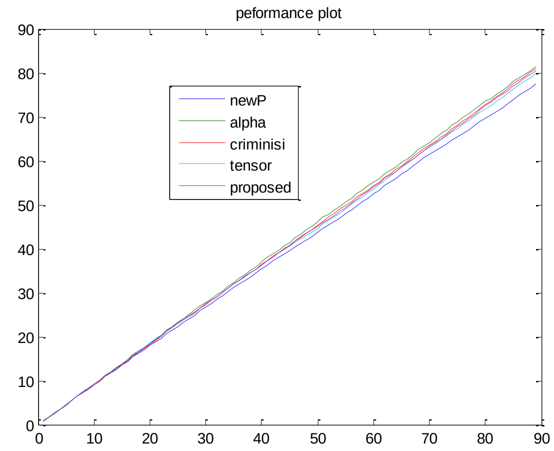

Fig14 Performance plots of Q for a data set of images.

Conclusions

The abundance and variations of types and styles of ancient constructions along with art and carvings provide us with lots of variations and case studies for Inpainting. The area of reconstructing these monuments is sensitive as well rich with opportunities owing to diversity. It is an attempt to bring about the image perception that has been damaged permanently, even though the numerical values such as PSNR along with few other quality measures to quantify the quality recovery, the perception to eyes has no replacement. Some portion of monuments if better lit then vicinity patches result in lower Quality factor but brighter view of reconstructed image. The method proposed here to determines the Filling Priorities based on statistical and spatial criterion performs better than other methods in many cases and has results comparable to standard methods for specific images. Grouping of pixels based on K means saves a significant time, improving the speed of reconstruction.

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