Digital Restoration of Damaged Mural images

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ABSTRACT

Patch-based techniques are proven to generate promising results and outperform many of the existing state-of-art techniques for most of the applications in digital image processing. In this work we develop a patch based coherent texture synthesis technique. A patch-based anisotropic diffusion techniques combined with a novel high-frequency generating technique that can enhance line/brush strokes is also proposed. Though these techniques can be applied to many different image processing applications, here we have limited ourselves in the application to interactive digital mural painting recovery/restoration. Some empirical and practical evidence for its high quality texture synthesis and restoration for mural paintings are also presented. The experimental results show the effectiveness of the proposed algorithm.

1. INTRODUCTION

The motivation of Heritage Preservation mission is based on the ideology that the art and artifacts of the past should be respected and cared for. A mural is a piece of artwork painted or applied directly on a wall, ceiling or any other large permanent surface. A particularly distinguishing characteristic of mural painting is that the architectural elements of the given space are harmoniously incorporated into the picture. Those paintings are important as they bring ancient art into the public sphere. Now a days those are being deteriorated rapidly and so it becomes a necessity to preserve what we have right now and also to restore it digitally so that we may have an idea of possible original appearance. Digitally restoration of archaeological objects is more useful and efficient because permanent change of the art-work from its present form is not allowed. Digital restoration through image processing techniques tries to generate the original look without actually changing the object. Therefore it is always advisable to restore art-works digitally. There are some expert artist who can restore digital art-works manually but with great perfection and take really long time. Moreover, this process of expert restoration is highly expensive. Here we attempt to develop an algorithm to restore the digital mural paintings almost automatically (little user intervention is required).

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ICVGIP '12, December 16-19, 2012, Mumbai, India
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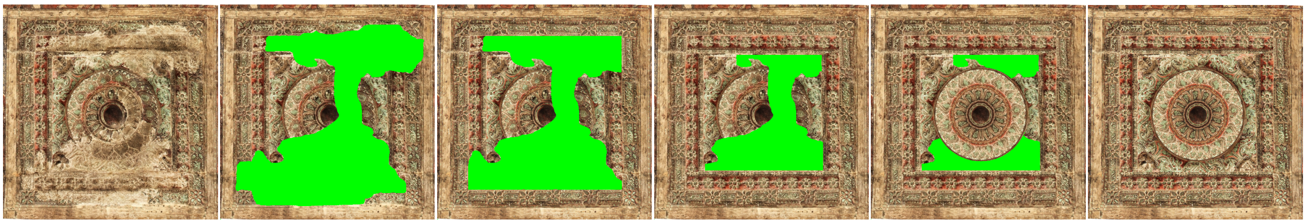
Initially, we tried to make a fully automatic system for digital mural restoration. However, because of the large variation observed in the typology of distortion, user interaction seems unavoidable. Rather, we develop algorithms that can be executed in real time, so that user can instantly observe the effect of the parameters or the constraints impose on the input image under study. Then he/she would intend to select, in an intuitive way, the values that produce the optimal visual and coherent result. Needless to say, in this case, only subjective optimality criterion can be used since no ground truth data are available for mural images.

In the classical image processing, people have been working on image restoration, more specifically image de-noising and de-blurring, during the last four decades. Recently, image inpainting or image completion receives more attention due to huge demand for automatic image completion and/or undesired object removal. Inpainting and completion are basically identical concept. The structure preserving small region filling algorithms are known as inpainting algorithms [8], [32], whereas the completion algorithms [16] fill large region(s) based on co-occurrence of patches inside the image and across the visually similar images in the database. Those algorithms work well for most of the natural images, but for paintings/mural images containing either smooth brush strokes or some repetitive texture pattern or some regions with only a few curves/lines, they may not be able to recover the pattern the way it should be. Moreover, it is always desirable to use more advance algorithm that can response on real time so that it can lead to an interactive user tool. In this work, we propose an algorithm for constraint coherence image completion that would be useful for the paintings having repetitive pattern where the user needs to mark the target (damaged) region together with the source (intact) texture region. In contrast, on the unconstrained version that are applied to the small regions of smooth texture requires the user to mark only the target region. Those are discussed in detail in the following sections.

To remove spurious noises, preserving edge/brush strokes of paintings, we need an edge preserving diffusion scheme. Moreover, we not only wish to preserve edge/brush strokes rather enhance it to synthesize more realistic sharp paintings. In this work we also propose a high frequency enhancing scheme in conjunction with a anisotropic diffusion.



(a) Original (b) After marking (c) step - II (d) step - III (e) step - IV (f) Final Output

Figure 1: Digital mural restoration: left to right are the original image and different steps of proposed texture synthesis on the marked region followed by a high-frequency generating diffusion which leads to the final output.

A patch-based diffusion technique based on Beltrami-kernel flow is used in an alternating sequence with a novel patch-based high frequency enhancing method which leads to an edge-sharpening anisotropic diffusion technique which is robust to noise.

Therefore hereby we enlist our contributions as follows:

- Present an algorithm for automatic fast coherent texture synthesis.
- Develop a patch-based edge enhancing anisotropic diffusion technique.
- Design a novel application for interactive mural painting restoration technique based on patch matching.

This paper is organized as follows. The following Section 2 describes some pioneer works in the field of painting restoration, image inpainting/completion and texture synthesis. Proposed coherent texture synthesis procedures are discussed in Section 3 where some practical evidences are also presented. Section 4 describes our edge-preserving anisotropic diffusion procedure. At the end, we show some experimental results in Section 5 and conclude with mentioning some future research directions in Section 6.

2. BACKGROUND

To address the problem of automatic digital paintings restoration, Giakoumis and Pitas [14] proposed some morphological operators to find out cracks followed by separation of brush strokes which have been misclassified as cracks and then the cracks were filled using seed growing approach. Later, they realized the necessity of user intervention and came up with an extended interactive algorithms in [13]. Recently Arora *et al.* [1] used the same tools for detection and filling the cracks and applied a color transformation to map the degraded color to the original restored color space. This color mapping is estimated from an existing database of original and degraded color image pairs. This class of works are applicable only to the paintings with some cracks and color distortion, certainly would fail on mural paintings containing significant amount distortions of the other kind. In such cases we need to have algorithms that can fill larger distorted or damaged portions by synthesizing texture.

Efros and Leung [11] proposed a texture synthesis method using a simple non-parametric sampling. Further improvement was done to modify the search and sampling approaches for better structure preservation [10], [33]. The greedy fill-in order of these algorithms sometimes introduces inconsistencies while to completing the large holes with complex structures. Wexler *et al.* [31] formulated the completion problem as a global optimization, thus obtaining more globally consistent completions for large missing regions become possible. Although this method produces excellent results, it is still relatively slow and has been demonstrated only on small images.

In the context of content-aware image resizing Avidan and Shamir [3] reduced the image by repeatedly removing vertical (top-bottom) and horizontal (left-right) curves least energy (called seam curve). Similarly they increased the size of the image by repeatedly including those curves. Some extensions [23], [27] of this algorithm are also developed and optimized for content-aware video resizing. These works are parameter-free and can produce excellent result in most of the cases. However in the applications like mural or painting restoration these do not readily fit well as our goal is to generate texture on the distorted region coherent to the undistorted regions rather than filling by the least energy pixel values.

3. COHERENT TEXTURE SYNTHESIS

Simakov *et al.* [24]have suggested a method to summarize the visual data using bi-directional similarity based on coherence of patches. They have used a global objective function that removes the pitfalls of local inconsistencies and the heuristics of using large patches. In this work, we incorporate the same idea to devise a new technique for synthesizing texture that is capable of filling the missing or distorted regions which are coherent to the known and undistorted parts of the image.

In our method, we assume that our missing/distorted region H of given input image I has coherence with the other parts of the image. i.e. we wish to complete the missing region H with some new data H^* such that resulting image $\hat{I}$ has as much as global visual coherence with the original undistorted image region $I \setminus H$. Therefore we seek a solution that maximizes the following objective function

$$Coherence(\hat{I} \mid I \setminus H) = \sum_{p \in H^*} \max_{q \in I \setminus H} s\left(\mathbf{P}(p),\ \mathbf{P}(q)\right) \quad (1)$$

where p and q run over all points of the corresponding portions, and $\mathbf{P}(p)$ denote the patch extracting operator around pixel location p and $s\left(\mathbf{P}(p), \mathbf{P}(q)\right)$ is the local similarity measure between patches around p and q. In our case we have considered the similarity measure as:

$$s\left(\mathbf{P}(p),\ \mathbf{P}(q)\right) = \exp\left(\frac{-d\left(\mathbf{P}(p),\ \mathbf{P}(q)\right)}{\sigma^2}\right), \quad (2)$$

where $d(\mathbf{P}(p),\ \mathbf{P}(q))$ is the square of the Euclidean distance between patches $\mathbf{P}(p)$ and $\mathbf{P}(q)$.

As eq. (1) is a non-linear objective function, we solve it iteratively using EM (Expectation and Maximization) like algorithm, where in each step the current guess is updated locally. The coherence between patches in H^* and rest of the image $I \setminus H$ as shown in eq. (1) is maximized if for every point $p \in H^*$ all the surrounding patches $[\mathbf{P}(p_1), \mathbf{P}(p_2), \ldots, \mathbf{P}(p_k)]$ agree on the pixel color at p with all corresponding location of $[\mathbf{P}(p_1), \mathbf{P}(p_2), \ldots, \mathbf{P}(p_k)]$ appear in the image $I \setminus H$. Therefore, the iterative E-step will aim at satisfying this condition at every point $p \in H^*$ and the M-step will search for the best similar patches in unaltered region $I \setminus H$ of the image I. Let $[\mathbf{P}(q_1), \mathbf{P}(q_2), \ldots, \mathbf{P}(q_k)]$ denote the patches in $I \setminus H$ that are most similar to $[\mathbf{P}(p_1), \mathbf{P}(p_2), \ldots, \mathbf{P}(p_k)]$. Then the predicted $\mathbf{P}(p_i)$ would be reliable if $s_i = s(\mathbf{P}(p_i),\ \mathbf{P}(q_i)) \approx 1$. Therefore at each iteration and for each point $p \in H^*$ and corresponding surrounding patch $\mathbf{P}(p_i)$, we need to find out best possible patch $\mathbf{P}(q_i)$ in $I \setminus H$. Then we replace the color at p by the weighted average of the color at the corresponding locations of the similar patches $\mathbf{P}(q_i)$. The weights are simply taken as the similarity measure s_i between the corresponding patches at p_i and q_i. Now the required huge computation of searching process for finding nearest neighbour (most similar) is reduced significantly by compensating it to approximate nearest neighbourhood (ANN). In the following subsection we describe an efficient search process [5].

To enforce the global consistency further and to speed up convergence, we perform the iterative process in multiple scales. Each of the scale makes the resolution a fraction of the resolution of the upper scale. Scaling factor $1.25 - 2.00$ can produce significant result in most of the cases. In all of our experiments, we have chosen resolution scale to be 1.5. The optimization is done by using EM technique starting at coarsest scale and the solution is propagated to finer levels for further refinement. H is initialized by some random values at the coarsest scale followed by a few EM iterations. Then, both H and $I \setminus H$ are gradually upsampled to finer resolutions, followed by more EM iterations, until the final fine resolution is obtained. This propagation is performed by finding the best matching patches in the current resolution level, and merging their higher resolution versions at the finer resolution. A formalism similar to eq. (1) was already used in [31] for summarizing visual data. In Fig. 3, we have demonstrated the performance of our algorithm. We observe that visually at some instants the result of Kwatra *et al.* [18] may look better than ours but our algorithm can preserve more coherent information than the other two methods. This coherency preserving nature of our algorithm is necessary and important aspects in certain applications where we need to give more emphasis on preserving the coherent information than making more visually attractive output.

In Fig. 2, we have shown the result of proposed texture synthesis for the problem of image inpainting/completion. It is clear from the images that our algorithm can retrieve the coherent information from the whole unaffected portions of the image. The structures are preserved in the coarser scale and the coherence information is embedded during the refinement into fine structure at the larger scale.

The efficiency of this algorithm can be improved in a various ways. We can impose constraint on the search space by selecting a region as a source region for searching similar patches. In that case the synthesized texture would have coherence with the source region only. With this little user intervention, the performance of texture synthesis improves significantly and user can get more control over the synthesizing process. If the synthesized texture is not satisfactory then the selected source region is refined. In Fig. 4, we have shown an example of constraint texture synthesis. In comparison to this the earlier method may be refined to as unconstrained texture synthesis.

Figure 2: Image inpainting/completion as an application of texture synthesis: The marked green regions (containing undesired objects) are replaced by most coherent patches of the unmarked region in the image.

Figure 4: Constraint texture synthesis for the application of mural image restoration: images in the top row are the source texture and bottom two rows are the synthesized textures of twice the size of original.

In the unconstrained version of the algorithm the source region considered as the whole image. The constraint tex-

Input (Olives) Efros and Leung [11] Kwatra *et al.* [18] ours

Figure 3: Demonstration of Texture synthesis: Proposed method preserves more coherent texture information than other methods. Left most one is the source texture image and rest images are the texture generated by different methods. The right-one is the result of our texture synthesis method which is more coherent with the source texture than the other methods.

ture synthesis is more efficient and fast (since we need to search for similar patches only on limited area) than the unconstrained one. However, sometimes we are not sure about the coherent source region and let the algorithm to search the whole image for coherent patch.

3.1 Local Similarity Measure

Nearest neighbour search is an important problem in a variety of applications, including the knowledge discovery and data mining, pattern recognition and classification. The task is to build a fast algorithm that could able to generate nearest neighbourhood field of every patches of an image. Obviously the problem can be solved in $O(dn)$ time through simple brute-force search for n points in d dimensional space. There are a number of existing optimal algorithm for approximate nearest neighbour (ANN) search [2], [17] that can solve the problem in $O(d \log n)$ or less time. Those algorithms are efficient and fast. However, in this work, we employ ANN search algorithm "PatchMatch" [5] [1] which works really well in the space of patches. This algorithm is mainly used for interactive image retargeting applications and has three main steps/subroutines. Initially the nearest neighbourhood is filled with either random offsets or using some prior information. Next, an iterative update process is applied to the ANN field, in which good patch offsets are propagated to the adjacent pixels, followed by random search in the neighbourhood of the best offset found so far. The key insight that drives the algorithm is that some good patch matches can be found via random sampling, and that natural coherence in the imagery allows propagating such matches quickly to the surrounding area. We found that the algorithm is reliable and efficient. Therefore incorporate this to generate the ANN field in our algorithm.

4. EDGE SHARPENING ANISOTROPIC DIFFUSION

Anisotropic diffusion was originally designed as edge preserving denoising process [21], [25], [28] capable of removing noise without reducing the edge strength. Here the images we deal with are noisy as well as distorted. So while removing noise we want not only to preserve edges but also to enhance edge strength. That is why in the second phase of processing we build an edge sharpening anisotropic diffusion. Therefore after generating the textures on the distorted region, we apply a diffusion scheme that can remove the spurious noise while sharpening the edges of painting strokes.

Following the success of the Nonlocal Means (NLM) denoising methods introduced by Buades *et al.* [7] much attention has been devoted to developing various types of patch based image processing applications [4], [12], [19], [26]. In fact anisotropic diffusion is also extended to the space of patches [22], [30].

In this section we develop a diffusion scheme by combining an existing patch based anisotropic diffusion method [22], [30] with a novel robust high-frequency generation algorithm. First, we give a brief account of patch-based anisotropic diffusion technique.

4.1 Beltrami-flow On Patch-Space

Let us define a Patch-Space $\mathbb{S}$ $(\subset \mathbb{R}^{nw^2+2})$ consisting of all the tuple of the form $(p,\ \mathbf{P}(p))$ where p is a pixel and $\mathbf{P}$ is an operator that extract a patch from an image I, $w \in 2\mathbb{N}+1$ is the window size or patch size and n is the number of channels in the image. Then we define a mapping $\mathbf{f} : \mathbb{R}^2 \rightarrow \mathbb{S}$ in the form

$$\mathbf{f}(p) = (p,\ \mathbf{P}(p)). \tag{3}$$

Now any point in patch-space can be written in the form $(p,\ \mathbf{P}(p)) \equiv (x,\ y,\ I^k(x+i,\ y+j)),\ \ i,j = -w/2 : w/2,\ \ k = 1 : n$, where $\mathbb{R}^2$ is the Riemann manifold. From hereon, for brevity we will denote $I^k(x+i,\ y+j)$ by $I^k_{i,j}$. Note that I^k is the simply k^{th} color channel. We wish to derive the induced metric tensor G for this new embedding. For that we first consider the arc-length measurement in the embedding space which we assume to be Euclidean and therefore

$$ds^2 =< df, df >= dx^2 + dy^2 + \sum_{i,j,k} (dI^k_{i,j})^2 \tag{4}$$

In reality, the coordinates x and y do not possess the same physical measure as the color values of the image so we need to introduce a scaling factor into the patch space metric

[1]Source code can be downloaded from http://gfx.cs.princeton.edu/pubs/Barnes_2009_PAR/index.php

given by

$$h_{ij} = \begin{cases} \delta_{ij} & \text{if} \quad i,j \leq 2 \\ \beta^2 \delta_{ij} & \text{otherwise} \end{cases} \tag{5}$$

where δ_{ij} is the Kronecker delta and $\beta < 1$ is a parameter that controls the trade off between the center pixel with other pixels of the patch. Using the chain rule $dI_{i,j}^k = I_{i,j,x}^k dx + I_{i,j,y}^k dy$ we pullback the metric from the embedding to determine that the induced metric tensor for the 2D image manifold embedded into patch-space is given by

$$G = \begin{pmatrix} 1 + \beta^2 \sum_{i,j,k} {I_{i,j,x}^k}^2 & \beta^2 \sum_{i,j,k} I_{i,j,x}^k I_{i,j,y}^k \\ \beta^2 \sum_{i,j,k} I_{i,j,x}^k I_{i,j,y}^k & 1 + \beta^2 \sum_{i,j,k} {I_{i,j,y}^k}^2 \end{pmatrix} \tag{6}$$

So a geometric flow of the manifold may be formulated as [30]

$$I_t = \delta_g I = \frac{1}{\sqrt{g}} div(\sqrt{g} G^{-1} \nabla I), \tag{7}$$

where $g = det(G)$, and δ_g is the second order differential operator of Beltrami which creates a scale space via the generalization of the Laplace operator onto Riemannian manifolds. In the following section we describe our robust high-frequency generation scheme.

4.2 High-Frequency Generation Through local Self-similarity

To develop an algorithm that can able to generate sharper edge on the boundary region and keep the smooth portions unaltered. In this regard, we learn the relation between each patch and corresponding sharp patch in the image. One naive way to do so is to learn the correspondence from a database of image pairs containing images of sharp boundary and corresponding blurred images. Then apply this knowledge to each patch on the target image to generate the corresponding sharp patch having high-frequency boundary. Recent studies on single frame Super Resolution [12], [15] suggest that patches in a natural image tend to redundantly recur many times inside the same image, both within the same scale, as well as across different scales. This patch similarity is more frequent in the image itself than in the database of different natural images. Here we show how similar ideas can be exploited within our single image High-Frequency (HF) generation framework without any external database or any prior example images. The patch correspondence can be learned directly from the image itself, by employing patch comparisons across multiple image scales similarly as is done for texture synthesis.

Let B, the blurring kernel related to our original image I, is assumed to be a small Gaussian kernel. Then our predicted sharp image $\hat{I}$ would be related with original image I as $I = (\hat{I} * B)$, where '$*$' simply denotes the convolution operator. We would find out the correspondence between the patches of I and the HF component $\hat{I} - I$ which is added later with the original image patch I to get the desired sharp patch. We could have learned the patch correspondence directly for the patches of I and $\hat{I}$ but we have seen experimentally that learning for I and $\hat{I} - I$, we can achieve better result.

We learn the correspondence from the image itself at different scales. Let $H_0(= I), H_1, H_2, \ldots, H_n$ denote the cascade of down-scaled image obtained from original image I, using small blurring operator followed by downsampling

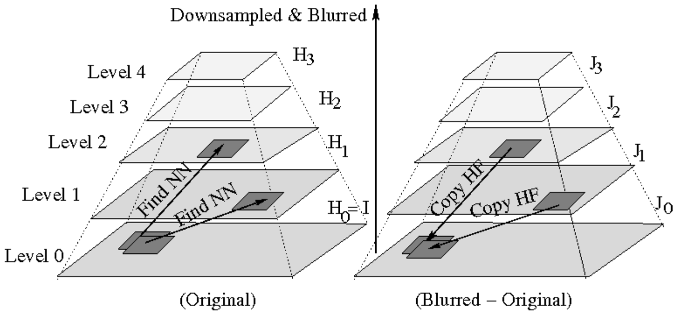


Figure 5: Generating high-frequency component: the left pyramid is generated by resizing the image into smaller scales. This is done by low pass filter with small kernel followed by downsampling with small resolution factor (usually taken as $1.25 - 2.00$). The right pyramid is build by applying some blur operator on down-scaled images and then subtract from original. This pyramid pairs stores the information about the correspondence between a blurred patch and actual high frequency components. The bottom image of the cascade in left pyramid is the original image and the same of the right pyramid is the corresponding HF component we wish to predict using patch matching technique.

with a resolution factor s. Those images are nothing but the re-sized images into smaller scales of the original image. Then we apply the blurring operator B on each of the cascade image H_l and subtract from the original ones. This lead to the HF component $J_i = H_l - (H_l * B)$ (we generate HF components J_l for $l > 0$ and J_0 is the component we want to predict) of the original down-scaled image H_l. In this way we generate the cascade of HF versions J_l corresponding to H_l. This cascade of images generation process is demonstrated in Fig. 5.

Let $\mathbf{P}_l(p)$ denotes a patch in the image H_l at location p. For any pixel $p \in H_0$ in the original image, we search for patches similar to $\mathbf{P}_0(p)$ within the cascade of low resolution images H_l (with the help of, say, search algorithm PatchMatch [5]). Let $\mathbf{P}_l(q)$ be the best matching patch found at the location q of the low-resolution image H_l and corresponding HF patch $\mathbf{Q}_l(q)$ is extracted from J_l at the location q. Then we copy this HF patch $\mathbf{Q}_l(q)$ to our unknown HF image J_0 at the location p. This basic step is illustrated in Fig. 5. We do this operation for all the overlapping patches and take simply an average on the overlapping region. Thus we generate the HF component J_0 and is added back to the actual input image I to get the HF enhanced image $\hat{I}$.

This process has two advantages over other high-pass operator [6], [29]: (i) It is robust to noise because noise are reduced significantly during the formation of down-scaled images and (ii) no spurious ringing artifacts are been introduced during HF generation process because we are taking average of all overlapping portions of the patches.

The HF generated diffusion scheme is obtained by alternating a few iteration of patch-based anisotropic diffusion and the proposed high-frequency generation algorithm for different kind of images. We have seen that $3 - 5$ iterations are sufficient to produce a good quality image. We can treat the number of iterations as user control parameter. User choose this parameter for which more visually appealing result/most realistic synthesized painting can be generated. An experimental result is shown in Fig. 6. We see that a significant amount of noise is reduced and the edges/brush strokes of the painting are enhanced significantly. As a result the processed painting looks more close to the possible original one than the given deteriorated version.

Figure 6: Result of proposed edge enhancing anisotropic diffusion scheme. Left-one is the original image and the right-one is the corresponding diffused image. It is clearly seen from the image that after diffusion the smooth regions gets more smoothed whereas edges are enhanced and sharpened.

5. EXPERIMENTS

We have implemented our algorithm using MATLAB 7.6 on a Linux OS with 8GB of RAM and a 3.6-GHz Intel processor. Mex codes for some of the subroutines are used to speed up the process. We have seen that even with reasonably large images our system responses in almost real time. Only for HF diffusion process it takes few seconds to generate the output.

We have already seen some results of our algorithm. In this section, we present some more examples. In the first example, we have shown the result of unconstrained texture synthesis followed by HF diffusion process [Fig. 7]. Here we have marked some distorted portions on the input image. Then our algorithm automatically finds out patches that are most coherent from the undistorted portion of the image. Then we apply HF generating diffusion scheme to so that the corrected image looks like more realistic painting.

In the next example, we have shown the result of constrained texture synthesis. Here again we mark the regions to be filled, and also select a source window and a target window around the marked region. The texture is generated on the marked region of the target window coherent to the texture of the source window and unmarked portion of the target window. If the synthesized texture is not satisfactory, user can apply undo process and select different source/target window and repeat the above process. In this work the source and target windows have either rectangular or circular shape as we observe that these shapes frequently occur in the mural paintings. However, this may be extended to allow the user to select the windows of any arbitrary shape according to his/her choice. For circular shaped source or target windows, we employ the similar concept of Daugman [9] used for identification of iris pattern. Here, we first transform it from Cartesian to polar coordinates. Then the texture is generated in the transform domain in a similar way as it is done for the rectangular window. Then we transform back to its actual coordinate system and replace the corresponding region.

In Fig. 8, top row contains original image and the marked region (in green) where texture to be generated. We select the source texture window by the red bounding box and corresponding target texture region by the blue bounding box. At each step the marked portion of the target window is filled by the texture that is coherent to the texture in the source window. Second row demonstrates the step-wise texture filling inside the marked region, where the steps are defined by the portion of marked region inside the target window. Third row is the transformed region of the selected circular region. Red bounding box denotes the source texture to be generated and next image shows the synthesized texture that is coherent to the texture inside the selected source bounding box. Fourth row shows the image after replacing the synthesized texture on the damaged region, i.e., after image completion followed by applying the proposed diffusion technique. In the bottom row we display the cropped portion of the original and the restored images. We have also included a number of results in the supplementary document.

6. CONCLUSIONS

In this work, we develop an algorithm for coherent texture synthesis and high-frequency enhancing diffusion scheme. Then using those as the building tools we develop a mural painting restoration technique which works in almost real time. Our experimental section suggests that we can achieve a close approximation of original realistic mural painting from the distorted ones. It would help artist to do the restoration process very quickly and amateur people can also restore efficiently as the user needs to select only some source and target windows where the texture is to be generated. Application of this idea of texture generation scheme and HF enhancing diffusion scheme may not be limited only to the paintings/mural restoration, and can be easily extended to other kinds of image restoration applications (e.g., image deblurring, de-noising, and super resolution). Hopefully, in future work we would address those problems in detail.

Figure 7: This is an experiment for unconstrained texture completion. Top row (left-right) Original input mural image, user marked the region should be filled and the final output after completion and followed by HF generating diffusion. The cropped portion of original image and output image at the corresponding locations are displayed in the bottom row. (This painting is downloaded from a digital painting storage website [20])

7. ACKNOWLEDGMENTS

This work was partially supported by DST, GOI (Grant no. . .) under the Indian Digital Heritage-Hampi Project.

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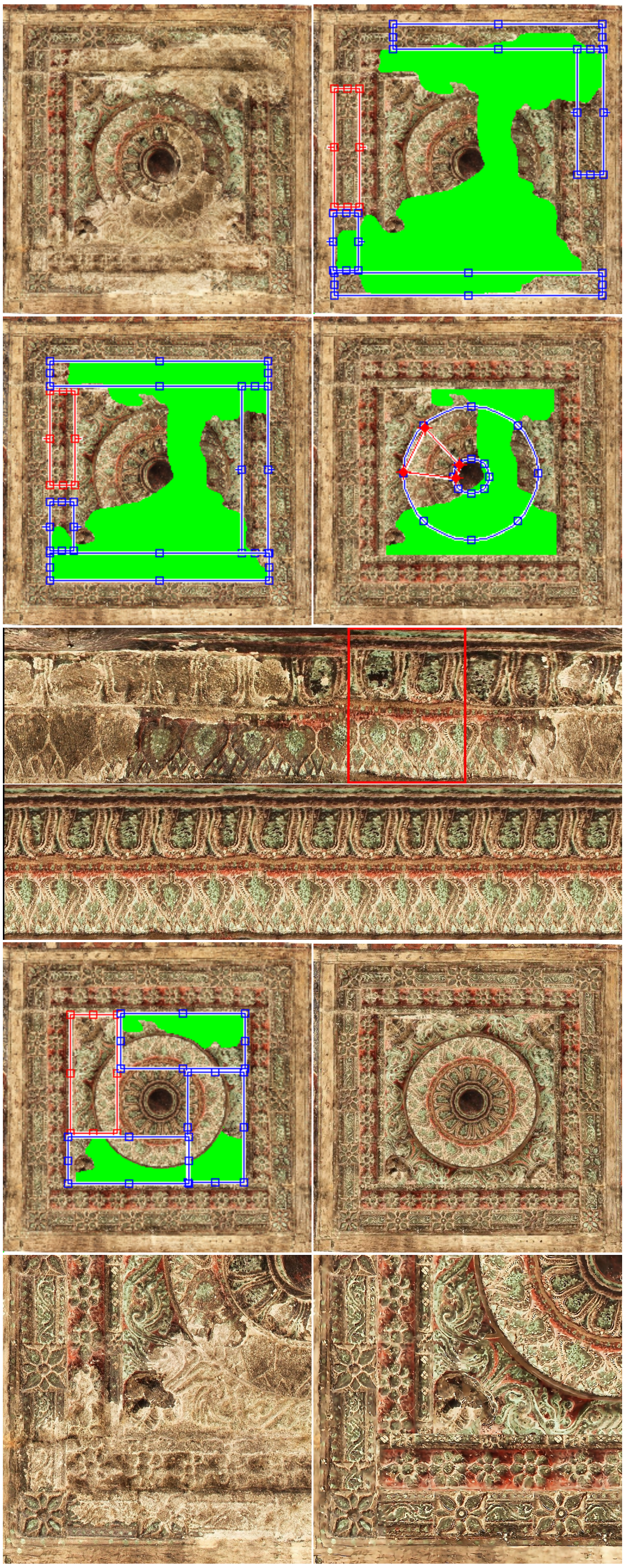

Figure 8: Illustrates the step-wise results of the experiment for constraint texture completion. See text for detailed description.

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