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An Efficient Exemplar Based Inpainting and Super Resolution Algorithm for Images

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Abstract: Image inpainting is one of the image renovation techniques used for reconstruction of lost or damaged region in an image. Images may contain corrupted and unwanted regions which are to be either removed or reconstructed. The main objective of the inpainting algorithm is to replace these regions and fill up the holes in a natural way. The method used for inpainting includes Exemplar based inpainting which generally works by removing the object and filling the hole by using the information extracted from the surrounding region of the same image. The proposed work aims at object removal and hole filling using Exemplar based inpainting which is further enhanced using Geometric Locally Adaptive Sharpening (GLAS) technique. The GLAS technique captures local image structure and sharpens the inpainted image without generating any noise intensification or over-sharpening effects by effectively combining denoising and sharpening methods. The results when compared with the traditional inpainting techniques outperforms in visual quality.

Key words: Exemplar based · GLAS · Image Inpainting · Object Removal · Reconstruction

INTRODUCTION

Image inpainting, also known as image fulfillment, is an effective research area in the image processing field. It can remove the unwanted parts of an image without affecting its overall structure. This kind of algorithm has become significant in the image processing community due to the various applications, such as object removal, or recovering the corrupted image(e.g., cracks in photographs, scratches and dust spots in film, old art work (for e.g. in museums), image editing, Stereoscopic image completion, completion of mural images, filling gaps in satellite images that occur due to instrumentation error and loss of data during transmission. Image Inpainting tries to create the original image but it is not possible without the prior knowledge of that image to extract information such as edges and texture. One of the requirement of inpainting is to have a mask which locates the places of an image where inpainting is needed that is done manually without using any mathematical equation. The goal is to produce a modified image in which the inpainted region is merged into the image so smoothly that a typical viewer is not aware that any modification has occurred by creating a visual pleasant continuation. It involves a number of theories and approaches in image completion [1], texture synthesis [2], image replacement, image interpolation, image deblurring, image search, etc. Majority of the algorithms like PDE based inpainting [3, 4], hybrid inpainting [4, 5] concentrate on images with smaller damaged portions. The holes can range from small, medium and large. The quality of performance drops as the mask size increases. Exemplar based method helps in reconstructing images based on the spatial information of the neighboring pixels. It is equally important to demonstrate the importance of background information in it. The background information can be any interesting scenes. Indeed, natural images are complex, consideration of shape, texture and colour information is required [2]. It is not possible to fill a portion which is not available in the original image. It performs well for larger mask size. They proceed by copying the patches and pasting inside the masked region to fill in, iteratively, by combining several pixels in an inpainting process. It is used to inpaint selected regions from an image. Therefore the objective is not to recover the whole image, but to create an image which has a closer coincidence with the original image. It provides impressive results in recovering textures and repetitive structures. In order to enhance the inpainted image, a different technique called GLAS (Geometric Locally Adaptive Sharpening technique) is

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used, it is able to capture local image structure and adjusting sharpening accordingly without creating any over-sharpening artifacts and the results are compared with single image super resolution technique called example based super resolution.

Related Works: Criminisis [6] contribution towards exemplar based algorithm is that they have explored a fill order which explicitly involves the propagation of linear structure (together with texture), the default favorite has been the onion peel strategy. It involves approaches such as the greedy approach which is also used in [7, 8, 9, 10] that inpaint the hole in one pass by copying multiple patches.

It avoids over-shooting artifacts that occur when image edges are allowed to grow indefinitely. Many methods have then been derived from these seminal works [11, 12, 13]. Alexander Wong and Jeff Orchard proposed a non-local means approach to exemplar-based inpainting [14]. An image with redundant content could have multiple samples within the image could be combined to form a more robust estimate of the missing information. They proposed that improved inpainting quality can be achieved using non local information. The target pixel is determined by using a weighted similarity function for each sample and are combined together to complete the missing information. The image inpainting techniques [3] fill holes in images by propagating linear structures (called isophotes in the inpainting literature) by diffusing the information from known region into the unknown region, as the algorithm progresses the contour evolves inward, so it is referred as the fill front. But it has a drawback, PDE cannot renovate the texture pattern and introduces blur effect while filling large holes. In [15] Robust Algorithm for Exemplar Based Inpainting is presented, they used a generic priority term to provide robust performance. Efros and Leung [2] have been the first to introduce the notion of image patches for texture synthesis. The core of their proposed method is the concept of the self-similarity prior. It synthesizes a texture by estimating the value of a pixel p according to a patch centered on it. It is found by searching the k-nearest neighbors according to the metric d = dSSD * G where dSSD is the vector of squared differences and G is a 2D Gaussian weighting kernel. Olivier Le Meur *et al*. [8] combined the way of both Exemplar with Partial Differential Equation (PDE) based technique by using structure tensors [16] to compute the priority of the patches to be filled. The main goal of this PDE based approach that helps in continuing both geometric and photometric information as described by the author Bertalmio *et al*. [3] by propagating the information in the direction using isophote lines. A novel inpainting algorithm proposed in [5] is able to fill holes in some kind of overlapping textures and cartoon image synthesis. Their algorithm is a direct extension of morphological component analysis that seperates texture and cartoon layers in a given image. Their approach differs from the one proposed by Bertalmio *et al*. [3] where image decomposition and filling-in stages were separated as two blocks. Their approach mainly concentrate on seperation, hole filling and denoising as unified task . Authors in [17] present an algorithm that unifies seperation, hole filling and denoising. Sparse representation have also been considered for solving the inpainting problem [10]. Known and unknown parts of the image are assumed to share the same sparse representation.

Proposed System: In this paper exemplar-based inpainting algorithm is described in detail which was initiated by Criminisi *et al*. in [6] and has been considered as a resource or reference for many of the patch based inpainting. Criminisi [6] approach and fast and enhanced algorithm for Exemplar inpainting [11] which combines both the texture synthesis and structure recreation with a few modifications are implemented. Texture synthesis based algorithms are one of the primitive method of image inpainting. Texture is the most continual portion of an image. This method introduces the concept of patching. The texture is to be synthesized by sampling, copying and joining together the patches from the similar texture sample of the original image. The goal is to produce a larger texture of the input sample taken from the known part of the image with a similar visual appearance. Exemplar based inpainting also resembles the texture synthesis based method. Generally, exemplar based image inpainting consists of the following steps:

Initialize the Target Region: In this step initial missing areas are marked and represented with colour. (i.e.here it is represented as R = 0, G= 255, B = 0).

Computing Filling Priorities: It is used to compute the priority function for all the unoccupied pixels at the starting point of each filling iteration.

Finding the Best Patch: In this the most analogous patch is found from the source area to compose the target region (i.e.in order to propagate the structure and texture information).This matching can be done using a suitable error metric called Mean Squared Error.

$$MSE = \sum \frac{(f_{x,y} - g_{x,y})^2}{N} \qquad (3.1)$$

where fx, y represents the element of the patch p and gx, y represents the elements of the patch for which MSE is to be calculated. N is the total number of elements in the patch.

Updating Image Information and Confidence Value: In this the boundary of the target area and filling priorities are updated.

Here are the terms that are used in the inpainting literature: a) The original image is represented as I.

- The target region (i.e., masked region) is represented as Ω
- The source region (i.e.., the region where the information is to be extracted) is represented as Φ. Φ = I-Ω
- The boundary of the target region is represented as δΩ.

Conversion to LR Image: The original image is down-sampled to an LR image in order to reduce the running time so that it can manipulate less no of pixels during inpainting. The time complexity is reduced while performing inpainting on an LR image compared to that of full resolution. A low-resolution image is less contaminated by noise and is composed by the main scene structure.

Creating Mask: It is a manual operation, the user only marks the region for inpainting and may mark more than one region that are spatially detached. The user selects the boundary of the region that he wants to inpaint by clicking on few of the points on the boundary by forming a dilated band that represents the target region and object is removed by making the confidence value of pixels in the target region as zero by creating a hole, then the hole is filled by calculating patch priority using exemplar based inpainting algorithm.

Patch Priority: Exemplar is capable of inpainting large regions, it replicates both texture and structure, the success of structure propagation depends on the order in which the filling proceeds. Finding the best candidate is fundamental for different reasons. In the first step, a filling priority is computed for each patch to be filled. The second step involves finding the best candidate based on the decreasing order of priority. The priority P(p) is computed for every border patch, patch is sought all over the image. Once all priorities has been computed, the pixel with highest priority is selected as the target pixel that imitates the appearance of the source region. Compute the priorities for a patch p centered at a point p for some p äÙ, its priority can be defined as the product of two terms [6]. P(p) = C(p) x D(p) where C(p) represents the confidence term for the patch and D(p)

$$C(p) = \frac{\sum_{q \in \Psi p \cap \Phi} C(q)}{|\Psi p|} \qquad (3.2)$$

$$D(p) = \frac{|\nabla I_p^{\perp} \bullet np|}{\alpha} \qquad (3.3)$$

where | Ψp | is the area of the patch, Ψp and α is the normalization factor (equal to 255 for a normal grey level image), np is a unit vector orthogonal to the front, δΩ at the point p and $\nabla I_p^{\perp}$ represents the perpendicular isophote at point p. np is found by finding the gradient for source region.

In this paper two important adjustments are considered that clearly improves the geometric coherence of the inpainted results: and reformulated the data-term, in order to better select the pixel candidates to fill in based on priority, source patches to be copied back to the masked hole, in a very efficient way(both in terms of visual quality and execution speed). The confidence term depends on how much reliable information is present in the patch. It is the sum of the confidence values for each pixel it covers for a patch. At the initial stage any pixel in the unknown area has a confidence value of 0 and all the pixels in the source area have confidence of 1. It assigns high filling priority, each pixel maintains a confidence value that represents our confidence in selecting that pixel. It tends then to inpaint first pixels having the most valid neighbors. This confidence value does not change once the pixel has been filled. The patches that are on corners of the fill front provide more relevant information against which to match the best patch. The patch with the highest value is selected to be filled next. This process is repeated until all the pixels have positive confidence values. The patch priorities are created by simply multiplying the confidence and structural factors(i.e., data term) for every patch. The data term gives high priority to pixels on the continuation of image structures (in green). It raises the priority of a block comprising an isophote line, an inpainting technique must attempt to continue the isophotes (line of equal gray value) as smoothly as possible inside the reconstructed region and the priority of selection of those patches that an isophotes flows into. The data-term Dp must tell about whether linear structures are present or not at a point p and with which angle they eventually crosses the region. The combination of the two terms produces the desired organic balance. The filling order computation helps in distinguishing the structure from texture. It is able to choose pixels that are continuations of lines/curves/edges and gives the desired result. Color information is also propagated inward from the region boundaries.Usually a higher priority indicates the presence of structure.The problem with the calculation of priority is that confidence term approaches small values quickly, this leads to incorrect filling order. They call this as the ”dropping effect”. The patches having higher data term are not selected due to this lowering of confidence value. This become noticeable when large regions are filled. Since, multiplication of priority term is sensitive to extreme values. So modifying this priority term to addition which is a linear function and also stable to unexpected noise and extreme values. P(p)=C(p)+D(p). Since the confidence term decays too fast, modifying this confidence term to a regularized term in order to match with that data term.

$$R_C(p) = (1 - w) \times C(p) + w,\ 0 \leq w \leq 1 \tag{3.4}$$

where ω is regularizing factor for controlling the curve smoothness. Using this confidence term the value of the confidence term is regularized to [ω, 1]. The new priority will now be defined as,

$$P(p) = \alpha \times R_c(p) + \beta \times D(p),\ 0 \leq \alpha, \beta \leq 1 \tag{3.5}$$

where and are respectively the component weights for the confidence and data term. Also $\alpha+\beta = 1$. and search for the best exemplar by using the coordinate.

$$\text{startX} = \max\left(0, p - \frac{n}{z} - c_r - \frac{Dx}{z}\right) \tag{3.6}$$

$$\text{startY} = \max\left(0, p - \frac{m}{z} - c_c - \frac{Dy}{z}\right) \tag{3.7}$$

$$\text{endX} = \min\left(w, p + \frac{n}{z} + c_r + \frac{Dx}{z}\right) \tag{3.8}$$

$$\text{endY} = \max\left(h, p + \frac{m}{z} + c_c + \frac{Dy}{z}\right) \tag{3.9}$$

where h and w are height and width of the image respectively, m and n are number of rows and columns in the patch and Dx and Dy are constants that represent the minimum diameter for the X and Y directions respectively and finding these coordinate using the maximum number of continuous green pixels in one row as well as column.

After replacing the patch, the confidence term is updated as C(p)=C(q), where c(q) represents the patch with maximum priority and select the patch with minimum mean square error from those patches with the same minimum mean square error, select the one with minimum variance. The above process continues until all the target pixels are filled. The result is the complete inpainted image.

Glas Technique: Here used a technique called geometric locally adaptive sharpening (GLAS) for image enhancement. It is able to sharpen the local image structure. Overshoot artifacts are avoided by adjusting the local sharpening parameter according to a robust sharpness measure. Then, the steering kernel (SK) regression technique is described which is able to capture local image structure even in the presence of blur and noise. Based on the SK, GLAS kernels are constructed and image restoration technique is developed. This approach can be applied to both gray scale and colour images for removing chrominance artifacts. SK obtain the local image structure by analyzing the estimated gradients. By using this structure information, it is able to determine the size and shape of a canonical kernel. Assuming a pixel of interest is located at position xi , its SK is mathematically represented as:

$$k(X_l - X_i) = \sqrt{\det(Cl)}\ \exp\text{-}(x_l - x_i)^T C_l(x_l - x_i) \tag{4.1}$$

where xl denotes a given location inside the SK window centered at xi and Cl is a covariance matrix estimated from a collection of gradients within an analysis window wl around xl a separate covariance matrix Cl is estimated and used at each pixel location. The local gradient matrix for the window wl centered at xl is defined as:

$$\begin{bmatrix} . & . \\ . & . \\ Gx(xm) & Gy(xm) \\ . & . \\ . & . \end{bmatrix}$$

where [Gx(xm), Gy(xm)] denote the image gradient at [xm, ym]. The dominant direction v1 and its perpendicular direction v2 within the region wl can be estimated by computing the (compact)singular value decomposition (SVD) of D:

$$D = U\Lambda V\ T = U \begin{pmatrix} s1 & 0 \\ 0 & s2 \end{pmatrix} (v1 \quad v2)$$

Here the singular values s1 = s2=0 represent the energy in the directions v1 and v2 respectively. The matrix Cl can then be stably estimated through the following formula,

$$C_l = \gamma(\varrho_1 v_1 v_1^T + \varrho_2 v_2 v_2^T)$$

$$\varrho_1 = \frac{s_1 + \lambda'}{s_2 + \lambda''}, \varrho_2 = \frac{1}{\varrho_1}$$

$$\gamma = \left(\frac{s_1 + s_2 + \lambda''}{M}\right)^\alpha$$

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where Q_l and γ are the elongation and scaling parameters, respectively. Λ' and λ'' are regularization parameters that dampen the noise effect and restrict Q_q and γ from becoming zero. M is the number of samples within the analysis window wl. The scalar α controls how strongly the size of the kernel will be affected by the local structure Once the steering kernel K is obtained, the geometric locally adaptive sharpening (GLAS) kernel S is build through the formula: S = K+ qL ? K where ? represents the convolution operator and L denotes a Laplacian filter. The positive scalar q determines the degree of sharpening. The restored image is then computed as a local regression (weighted average) with the kernel S as follows:

$$\hat{f}(x_i) = \frac{\sum_{x \epsilon w_l} S(X - X_i) g(X)}{\sum_{x \epsilon w_l} S(X - X_i)}$$

where g is the measured blurry and noisy image. The local metric Q for the pixel located at xl is defined as;

$$Q = S_1 \frac{S_1 - S_2}{S_1 + S_2}$$

To avoid overshoots in already sharp edges, set the values of the parameter q for a given pixel as a function of the local value of Q as follows;

$$q = \begin{cases} \beta, & if\ Q \leq T1 \\ \dfrac{\beta(Q - T2)}{T1 - T2}, & if\ T2 > Q \geq T1 \\ 0, & if Q \geq T2 \end{cases}$$

Given an RGB image g, transform it into YCbCr format gY, gCb, gCr and estimate steering kernel K and local sharpness metric Q at each pixel of the luminance channel gY. Construct GLAS kernels for the luminance channel with a spatially adaptive q according to local blurriness Q through (9) and (12) and restore the luminance channel to get $\hat{f}$ Y using (10). Construct GLAS kernels for the luminance channel with a small constant q and apply these to restore $\hat{f}$ Cb, $\hat{f}$ Cr through (10). Combine $\hat{f}$ Y, $\hat{f}$ Cb, $\hat{f}$ Cr to obtain the estimated RGB image $\hat{f}$.

Comparison with Super Resolution: Super resolution aims to generate high resolution from one or multiple LR images. In this paper single image example based approach generates high resolution from a single LR image. Conventional example based SR were strongly based on prior information and is classified into two categories. Implicit priori based SR represent prior through training images. Most k-nearest neighbour algorithms are implicit they search k-nearest neighbour to estimate HR image. The another category explicit based SR are either dictionary based that represent the priori by using LR-HR dictionary pair or it uses regression function to map the correspondence between LR-HR image pairs by either supervised or semi supervised learning process. Here Kernel Ridge Regression (KRR) is used that scans the input image with a small window and produces a patch valued output for each pixel output location. This produces a set of candidate images that reflects different local information. An output is obtained as a combination of candidates at each pixel based on estimated confidence of candidates. A sparse solution is obtained by combining kernel matching pursuit and gradient descent. The results are post processed using a natural image prior. Adopting the framework of Freeman *et al*. [19], estimate the corresponding missing high frequency (Y)detail by interpolating into the desire scale by using cubic spline interpolation. The estimation of high frequency(Y) is based on the laplacian of interpolation(X). The estimated confidence can then be added to the interpolation to generate the super resolved image. Instead of of generating a single image at once, a set of candidate estimate(Z) is obtained based on different local information of input image and contains partial information of the high resolution image and single image is obtained as a combination for each pixel of the set of candidate pixels. To enhance the visual quality around the edges, the results are post processed by using a prior model of natural images. In comparison to the multiple image SR, in single image super resolution[18] [19], the problem is severely under constrained because less information about the scene is provided.

The downsampled LR images are resized to the target HR image. The LR test images are super-resolved by a scale-factor of S = 2, 3 and 4. All the experiments were carried out using Matlab R2014.

RESULTS AND DISCUSSION

Generally large areas with lots of information are harder to reconstruct, because information in others parts of an image is not enough to fill those regions by satisfying both speed and quality is also a difficult task in inpainting. As inpainting is an iterative process, each patch selection depends on the previous iteration as shown in the figure.

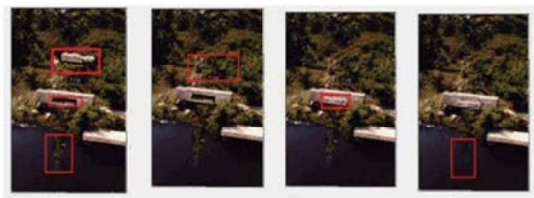

Fig. 1: Multiple iterations of Inpainted Image

Generic images are generally used for inpainting. Our test images are taken from the previous literature on inpainting and texture synthesis. Structure such as the shoreline, edge of the house are propagated into the target region very well along with plausible textures of shrubbery, water and roof tiles; Notice how the isophotes hitting the boundary of the target region are propagated inwards as shown in the figure.

The Glas technique is training free. Here the edges are sharpened while artifacts are sup- pressed edges and texture patterns are coherently enhanced and applied our algorithm to many test images ranging from simple to complex texture.

Performance Measure: The quality assessment of inpainted image is another difficult issue as there are no quantitative metric exist. The subjective assessment can be made to evaluate the inpainted image whether it is visually pleasing or plausible. However the running time is calculated for the execution of exemplar based inpainting for some of the test images as shown in figure.

For the enhanced image, a measure based on the Mean Square Error and the Peak Signal- to-Noise Ratio is used for measuring the quality of the enhanced image. The data loss is measured by Mean Square Error by comparing the pixel values of the noisy image and the enhanced image. As the PSNR is derived from MSE and it is used to measure the image quality. For color images with three RGB channels per pixel , the PSNR calculation is the same the only difference is that the MSE is the sum overall square differences divided by the image size and by three. In colour image the image is converted to a different colour space and PSNR is noted against each channel of that color space, e.g., YCbCr. The mathematical representation of the PSNR is as follows:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2$$

$$PSNR = 10.\log_{10}\frac{MAX_I^2}{MSE}$$

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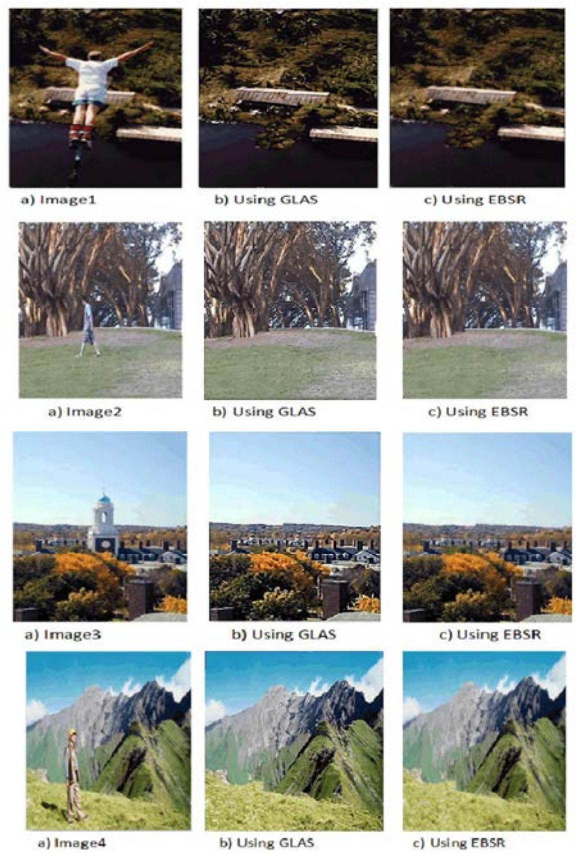

Fig. 2: Test Images

Here,
f represents the matrix data of our original image;
m represents the numbers of rows of pixels of the images;
n represents the number of columns of pixels of the image;
i represents the index of that row;
j represents the index of that column;
MSE_f is the maximum signal value that exists in our original "known to be good" image.Thus the performance measures are evaluated and the results are produced in the form of tabulation in Table 1.

Table 1: Running Time and PSNR Values

Image	Size of the LR Image	Running Time of Exemplar(sec)	PSNR Value of GLAS	PSNR Value of EBSR
Image 1	245×175	90	32.5122	30.0016
Image 2	275×230	40.39	30.1562	27.3889
Image 3	255×185	3.71	35.0048	30.4143
Image 4	240×210	25.88	33.5048	29.0006

CONCLUSION

Texture Synthesis and Exemplar Based Algorithms are mostly used for the purpose of inpainting. The success of the inpainting algorithm lies in how well the information (photometry), colour, shape and the structure (geometry) are propagated into that missing area. Our goal is to enhance the resolution and the quality of the inpainted areas using GLAS technique and the results also compared effectively with example based super resolution. Future work is knowledge of background information which includes edge continuity, neighboring object information, knowledge of distinction between two different objects in image or between object and background should be added when copying patch to make this algorithm intelligent. This approach can be extended for inpainting objects in videos and could be implemented on mobile devices.

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