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Assessment and Comparison of Image Inpainting Algorithms

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Abstract

Image inpainting refers to the process of restoring missing or damaged areas in an image. Numerous and different types of approaches have been proposed with varying applicability in restoring images from scratches or text overlays, loss concealment in a context of impaired image transmission, object removal in a context of editing, or disocclusion in image-based rendering (IBR) of viewpoints different from those captured by the cameras. In this article, it is tried to survey the most suitable and pleasing method among different algorithms of image inpainting that with the advent of sparse representations and compress sensing, sparse priors have also been considered for solving the inpainting problem. Diffusion-based techniques are better suited for filling large texture areas. The image (or the patch) is in this algorithm assumed to be sparse in a given basis [e.g., discrete cosine transform (DCT), or wavelets]. With this goal that an inpainted image is as physically plausible and as visually pleasing as possible.

Keywords: *image inpainting, object removal, diffusion-based inpainting.*

1. Introduction

Long before inpainting term has been used in Digital Images, it was used by artists of museum reconstruction. For example, restoring ancient paintings or old images, one area in an image or frame has been missed or damaged as a result of scotches, or ….. Over the recent years, high advance in the context of inpainting has been observed that boosted by numerous applications: restoring images from scotches or text overlays, loss concealment in a context of impaired image transmission, object removal in a context of editing, or disocclusion in image-based rendering (IBR) of viewpoints different from those captured by the cameras[1]. Although earlier work dealing with disocclusion has been published in [2]. Image inpainting is an ill-posed inverse problem that has no well-defined unique solution. To solve the problem, it is therefore necessary to introduce image priors. Known and unknown parts of the image are in this algorithm assumed to share the same sparse representation. The Previous methods including Diffusion-based method require implementing iterative numerical methods (isotropic or anisotropic) that are generally quite slow[1]. Straight lines, curves, and filling small regions are well suited for inpainting piecewise smooth images, they are not well suited for textured images, especially if the region to be completed is large [Figure1].

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Figure1: Typical blurring effects of (a) and (b) diffusion-based methods when the hole to be filled in is large which is followed by a blur.

Exemplar-Based Techniques work amazingly well in textured regions with homogeneous or regular patterns. The goal is to create a texture from a given sample, in such a way that the produced texture is larger than the source sample with a similar visual appearance. Nevertheless, they are not so well suited for preserving edges or structures, or for images with many small distributed holes [Fig. 2].

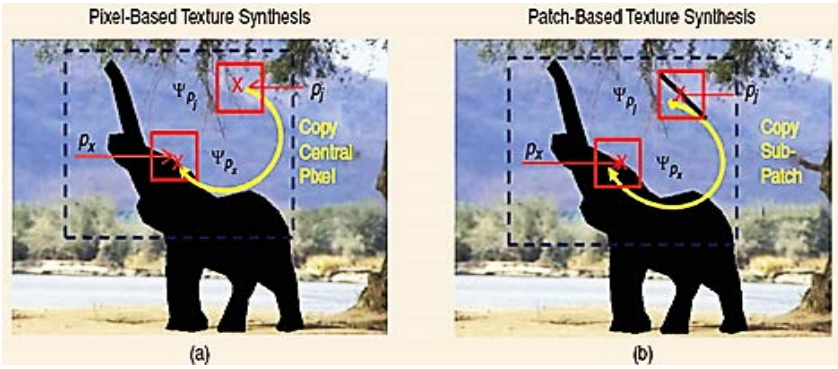

Figure2: The principle of exemplar-based methods: search for the patch the most similar to the known part of the input patch to be completed and copy the central pixel for (a) pixel-based approaches or (b) a set of pixels for patch-based approaches.

2. Sparse-Based Method

An image I can be mathematically defined as

$$\mathrm{I}:\left|\begin{array}{l}\Omega \subset \mathcal{R}^n \rightarrow \mathcal{R}^m \\ \mathrm{x} \rightarrow \mathrm{I}(\mathrm{x}),\end{array}\right. \tag{1}$$

Where x represents a vector indicating spatial coordinates of a pixel, p_x which in the case of a two-dimensional (2-D) image (n=2) is defined as x = (x,y) In the case of a color image, each pixel carries three color components (m=3)= defined in the (R G B) color space. Each color channel of I is denoted I_c: Ω →R In the inpainting problem, the input image I (i.e., each color channel of the image) is assumed to have gone through a degradation operator, denoted , M which has removed samples from the image. As a result, the generic definition domain X of the input image I can be seen as composed of two parts: Ω = S u U, S being the known part of I (source region) and U the unknown part of , I which we search to estimate. The observed degraded version F of the image can also be expressed as .F = MI. The goal of inpainting is to estimate the color components of the pixels p_x located at each position x in the unknown region, U from the pixels located in S the known region, to finally construct the inpainted image. The inpainting problem can also be solved assuming image sparsity priors. In this case, the image I is assumed to be a sparse-land signal [3], meaning that the image I is sparse in a given basis.

The basis can be formed by predefined elementary waveforms (also called atoms) which are stored in a dictionary matrix A. The dictionary matrix A can also be learned using dictionary-learning methods.

An image I is said to be k-sparse in a given basis stored in the dictionary matrix A, if it can be represented by a vector v having only k nonzero elements (i.e., its /0 norm is $||v||_o$=k) verifying I = Av. The sparsity of a signal depends on the considered basis, i.e., of the matrix A. Considering the degraded image F = MI, the inpainting problem is therefore formulated as searching for the sparse representation vector v of the image F, by solving

$$\min || v || 0$$

$$\text{such that:} \quad F = M\,A\,V. \qquad (2)$$

Many solutions exist for searching for the sparse vector v, with the most popular ones belonging to the family of greedy matching pursuit algorithms. A good overview of these matching pursuit algorithms can be found in [3, Ch. 3].

The above inverse problem is usually solved patch-perpatch rather than directly on the entire image F. For each patch Ψ_{px} of the image F formed by a known part Ψ^s_{px} and an unknown Ψ^U_{px} , one searches for the sparse vector v_{px} ,which best approximates the known part of the input patch Ψ^s_{px} as $\Psi^s_{px}= A^S v_{px}$ where A^S is a matrix obtained by masking the rows of the matrix A corresponding to the positions of the unknown pixels Ψ^U_{px} in Ψ_p , as shown in Figure 3.

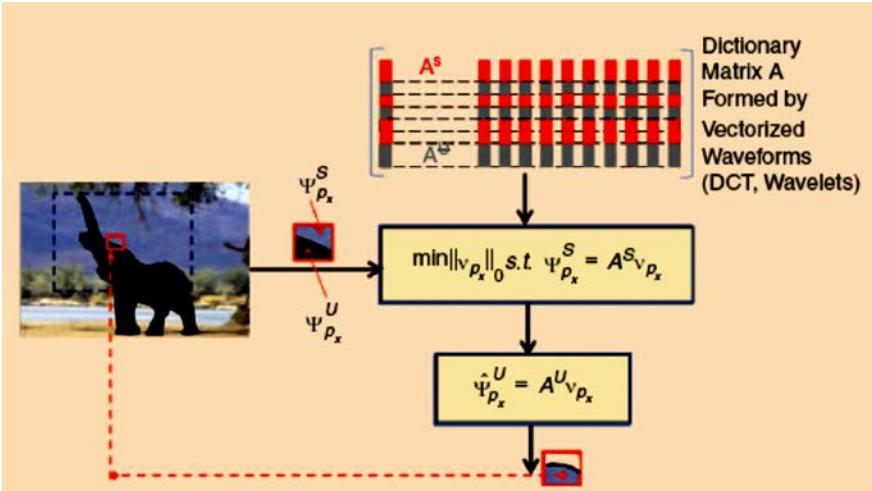

Figure 3: estimation of unknown pixels with sparse priors in transform domain. A dictionary matrix is constructed from waveforms (DCT, wavelets). The grey part of the columns of the dictionary represents the masked rows corresponding to the position of the unknown pixels in the input patch.

The same sparse linear combination of atoms is then used to approximate the unknown pixels Ψ^U_{px} as $A^U v_p = \Psi^U_{px}$, taking this time the masked samples of the atoms (these samples correspond to the positions of the unknown pixels). This general formulation is also used for other image processing problems like denoising and super resolution. The sparse representation area has recently evolved into the more general compressive sampling framework that also naturally applies to image recovery problems.

Variants have been introduced exploiting sparsity priors. Assuming that images are composed of locally uniform regions separated by edges, the author in [1] uses adaptive sparse representations. The algorithm performs a nonlinear approximation with adaptively determined sparsity constraints. Hybrid sparse representations enforcing both local and nonlocal sparsity are considered in. The nonlocal sparsity is defined as the sparsity of a three-dimensional (3-D) data array formed by the input patch

and its K -NN in the known part of the image, whereas the local sparsity is defined as the sparsity of the 2-Dpatch, the sparsity constraints being enforced by hard-thresholding in a predefined waveform basis (DCT, fast Fourier transform). Local and nonlocal sparse representations are then combined via Bayesian model averaging to satisfy both constraints of local smoothness and nonlocal similarity, with a constraint of fidelity to the known samples.

Patch-based methods [1] show that texture patches can be relevant dictionary elements. Therefore, instead of using predefined waveforms, a linear combination of candidate patches regularized by a sparseness prior on the weighting coefficients can be used for inferring the unknown pixels. Sparsity is also used in for determining structural patches to be processed first, as explained in the section "Patch Processing Order." The patch sparse representation is moreover constrained by local patch consistency.

2.1. Hybrid methods separating structure from texture

As said before, diffusion methods are appropriate for piecewise smooth images and for propagating strong structures. But they are unable to restore texture. On the contrary, exemplar-based methods work amazingly well in textured regions with homogeneous or regular patterns. Nevertheless, they are not so well suited for preserving edges or structures, or for images with many small distributed holes.

Yet, natural images contain composite structures and textures. The structures constitute primal sketches of an image (e.g., edges, corners) and textures are regions with homogenous patterns or feature statistics. To handle composite textures and structures, it is therefore natural to combine different types of approaches. Two main strategies have been considered. The first strategy consists in first separating the image components (texture and structure), and inpainting them separately with the most suitable method (e.g., diffusion or exemplar-based). The two inpainted components are then added together as in [6]. A second strategy consists of combining different approaches in one unique energy function using a variational formulation.

2.2. structure/texture separation

Structure can be identified in a supervised way where the user specifies curves corresponding to important missing structures (e.g., object boundaries) in the unknown region. A structure propagation is then performed by copying patches located in the direction of these curves in the known region. The remaining unknown pixels are in a third step estimated using a texture synthesis method.

Texture and structure can also be separated in an automatic manner, using, for example, a variational method as in [6], where the authors decompose the image as a sum of two functions, one being of BV representing the image structure, and a second one capturing the texture. The structure image is a sketchy approximation of the input image, containing only edges separating smooth regions. These piecewise smooth images are also referred to as cartoon images in [6]. In [6], the texture layer is inpainted using the texture synthesis method of [7] while the geometric layer is inpainted using the diffusion method, and the two inpainted components are added together to produce the final result.

Another method based on sparse representations for decomposing the image into a texture and a geometry component, called layers. Using two dictionaries of different characteristics A_g and A_t , the image is decomposed into structural and textural components as $I= A_g v_g+ A_t v_t$. The method is called morphological component analysis (MCA)[1]. The two dictionaries are mutually incoherent, i.e., each dictionary gives a sparse representation for one component while yielding a nonsparse representation for the other component. Both dictionaries are grouped into a big dictionary which is then used by a basis pursuit algorithm to find the sparse representation of each layer. The authors in [1] propose an algorithm based on this sparsity seeking image separation into two components. Instead of a separate processing of the two components as in [6], the sparse vectors for the two components are obtained by minimizing:

1. Morphological Component Analysis

$$\min||v_g||p+||v_t||p$$

Such that:

$$F = M(A_g v_g + A_t v_t) \quad (3)$$

where || 0 | | p denotes the L_p norm, with p often equal to zero or one. To solve this minimization problem, the constraint is introduced as a penalization term. TV penalization term is added to regularize the sparse approximation of the image geometry. This approach can fill in a region with composite textures and structures. It however introduces blur when the missing region is large. The patch sparse representation is moreover constrained by local patch consistency.

3. Application

Another natural application of inpainting is image editing in which the user removes objects, hence, uncovering unknown parts of the image foreground. This application is well illustrated by the images of Figure 4 in which one foreground object has been removed, leaving a hole to be filled.

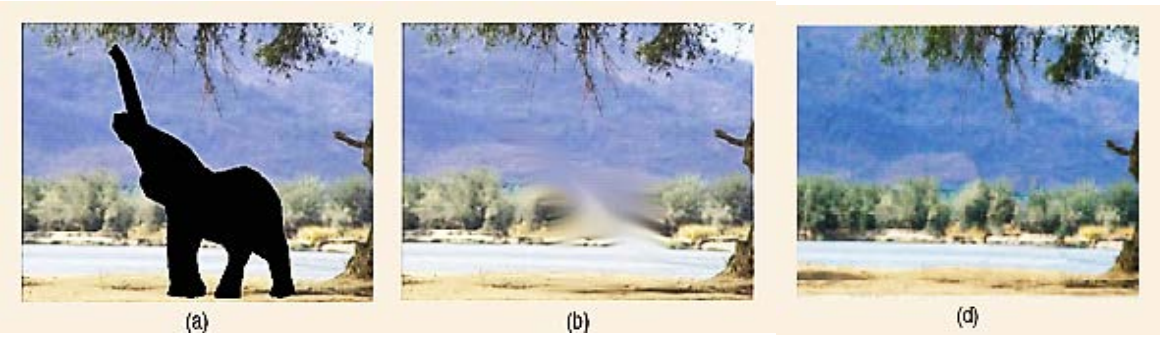

Figure 4: object removal application (a) mask and inpainting results with methods from different categories, (b) anisotropic diffusion, (d) patch sparse representation

CONCLUSION

In this article, one inpainting algorithm in Digital Images are proposed. Sparse-Based Method is better suited than different algorithms for recovering the texture of the hole. Features, applications and a taxonomy of inpainting methods are given in table 1. As the quality assessment of inpainted images is another open and difficult issue (as no quantitative metrics exists), therefore one has to rely on a subjective assessment to evaluate whether the inpainted images are visually pleasing and physically plausible.

Table 1: a taxonomy of inpainting methods

FEATURES	PDE-BASED DIFFUSION	EXAMPLAR-BASED INPAINTING	HYBRID METHODS	GLOBAL
PRIORS	SMOOTHNESS	SELF-SIMILIARITY,SPARSITY	SMOOTHNESS+ SIMILIARITY/SPARSITY	STATISTICAL, LOW RANK
OPTIMIZATION	GREEDY	GREEDY OR GLOBAL	GREEDY OR GLOBAL	GLOBAL
SENSITIVITY TO SETTING	LOW	HIGH	HIGH	HIGH
HOLES	SMALL	MEDIUM TO BIG	MEDIUM TO BIG	SMALL TO MEDIUM
APPLICATIONS	RESTORATION	RESTORATION,EDITING,DISOCCLUSION,CONCEALMENT	RESTORATION,EDITING, DISOCCLUSION,CONCEALMENT	RESTORATION

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