The Examplar-based Image Inpainting algorithm through Patch Propagation

Pranali Dhabekar, Geeta Salunke

Abstract—This paper presents a novel and efficient examplar-based inpainting algorithm through investigating the sparsity of natural image patches. Two novel concepts of sparsity at the patch level are proposed for modeling the patch priority and patch representation, which are two crucial steps for patch propagation in the examplar-based inpainting approach. First, patch structure sparsity is designed to measure the confidence of a patch located at the image structure (e.g., the edge or corner) by the sparseness of its nonzero similarities to the neighboring patches. The patch with larger structure sparsity will be assigned higher priority for further inpainting. Second, it is assumed that the patch to be filled can be represented by the sparse linear combination of candidate patches under the local patch consistency constraint in a framework of sparse representation. Compared with the traditional examplar-based inpainting approach, structure sparsity enables better discrimination of structure and texture, and the patch sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding textures.

Index Terms—Image inpainting, patch propagation, patch sparsity, sparse representation, texture synthesis.

I. INTRODUCTION

Image inpainting refers to filling in missing or damaged regions (like cracks or scars) in images. In fine art museums, inpainting of degraded paintings is traditionally carried out by professional artists and usually very time consuming, not to mention the risk of completely destroying a precious and world-unique ancient painting due to direct retouching.

Inpainting, the technique of modifying an image in an undetectable form, is as ancient as art itself. The goals and applications of inpainting are numerous, from the restoration of damaged paintings and photographs to the removal/replacement of selected objects.

Automatic digital inpainting is a technique which restores damaged image by means of image interpolation. The technique can be used in photo restoration (e.g., scratch removal), zooming, image coding, wireless image transmission (e.g., recovering lost blocks), and special effects (e.g., removal of objects). Current techniques may base on the extrapolation of neighboring pixels, recovery of edges, curvature-driven diffusions (according to the connectivity principle in vision psychology), and inpainting from multiple view points (i.e., image from movie, or image from different time and view point).

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* Correspondence Author
Pranali Dhabekar*, Department of Electronics and Telecommunication, Pune University, Genba Sopanrao Moze College of Engineering, Balewadi, Pune (M.H), India.
Geeta Salunke, Department of Electronics and Telecommunication, Pune University, Genba Sopanrao Moze College of Engineering, Balewadi, Pune (M.H), India.

II. LITERATURE REVIEW

The most fundamental inpainting approach is the diffusion based approach, in which the missing region is filled by diffusing the image information from the known region into the missing region at the pixel level. These algorithms are well founded on the theory of partial differential equation (PDE) and variational method. Bertalmio filled in holes by continuously propagating the isophote (i.e., lines of equal gray values) into the missing region.

Chan and Shen proposed a variational framework based on total variation (TV) to recover the missing information. Then a curvature-driven diffusion equation was proposed to realize the connectivity principle which does not hold in the TV model. Recently, image statistics learned from the natural images are applied to the task of image inpainting. The diffusion-based inpainting algorithms have achieved convincingly excellent results for filling the nontextured or relatively smaller missing region. However, they tend to introduce smooth effect in the textured region or larger missing region.

The second category of approaches is the examplar-based inpainting algorithm. This approach propagates the image information from the known region into the missing region at the patch level. This idea stems from the texture synthesis technique proposed, in which the texture is synthesized by sampling the best match patch from the known region. However, natural images are composed of structures and textures, in which the structures constitute the primal sketches of an image (e.g., the edges, corners, etc.) and the textures are image regions with homogenous patterns or feature statistics (including the flat patterns). Pure texture synthesis technique cannot handle the missing region with composite textures and structures. Bertalmio proposed to decompose the image into structure and texture layers, then inpaint the structure layer using diffusion-based method and texture layer using texture synthesis technique. It overcomes the smooth effect of the diffusion-based inpainting algorithm; however, it is still hard to recover larger missing structures. Criminisi designed an examplar-based inpainting algorithm by propagating the known patches (i.e., examplars) into the missing patches gradually. To handle the missing region with composite textures and structures, patch priority is defined to encourage the filling-in of patches on the structure. Wu proposed a cross-isophotes examplar-based inpainting algorithm, in which a cross-isophotes patch priority term was designed based on the analysis of anisotropic diffusion. Wong proposed a nonlocal means approach for the examplar-based inpainting algorithm. The image patch is inferred by the nonlocal means of a set of candidate patches in the known region instead of a single best match patch.

More examplar-based inpainting algorithms were also proposed for image completion. Compared with the diffusion-based inpainting algorithm, the examplar-based inpainting algorithms have performed plausible results for inpainting the large missing region.

III. RELATED WORK

A. *Patch Propagation*

In our proposed algorithm, the examplar-based inpainting algorithm through patch propagation. The two basic procedures of patch propagation are:

- Patch selection
- Patch inpainting.

In the patch selection, a patch on the missing region boundary with the highest priority is selected for further inpainting. The priority is defined to encourage the filling-in of patches on structure such that the structures are more quickly filled than the textures, then missing region with composite structures and textures can be better inpainted. Traditionally, the patch priority is defined based on the inner product between isophote direction and the normal direction of the missing region boundary.

In the patch inpainting, the selected patch is inpainted by the candidate patches (i.e., examplars) in the known region. The approach in Criminisi's examplar-based algorithm, P. Perez, and K. Toyama utilizes the best match candidate patch to inpaint the selected patch. The approach Wong's examplar-based algorithm uses a nonlocal means of the candidate patches for robust patch inpainting.

B. *Patch Sparsity*

To better address the problems of patch selection and patch inpainting, two novel concepts of patch sparsity of natural image, are proposed and applied to the examplar-based inpainting algorithm.

- Patch Structure Sparsity
- Patch Sparse Representation

C. *Patch Structure Sparsity*

We define a novel patch priority based on the sparseness of the patch's nonzero similarities to its neighboring patches. This sparseness is called structure sparsity. It is based on the observation that a patch on the structure has sparser nonzero similarities with its neighboring patches compared with the patch within a textured region. Compared with the priority defined on isophote, this definition can better distinguish the texture and structure, and be more robust to the orientation of the boundary of missing region.

D. *Patch Sparse Representation*

To inpaint a selected patch on the boundary of missing region, we use a sparse linear combination of examplars to infer the patch in a framework of sparse representation. This linear combination of patches are regularized by the sparseness prior (regularization) on the combination coefficients. It means that only very few examplars contribute to the linear combination of patches with nonzero coefficients. This representation is called patch sparse representation. The patch sparse representation is also constrained by the local patch consistency constraint.

This model extends the patch diversity by linear combination and preserves texture without introducing smooth effect by sparseness assumption.

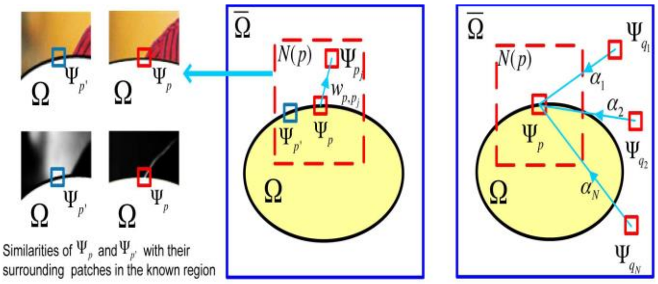
In summary, the structure sparsity and patch sparse representation at the patch level constitute the patch sparsity. The patch structure sparsity is inspired by the recent progress on the research of sparseness prior of natural image. The previous sparseness prior generally models the sparseness of image's nonzero features, e.g., gradients or filter responses. This kind of sparseness prior has been successfully applied to the image denoising, super-resolution, inpainting, deblurring and so on. The structure sparsity also models the sparsity of natural image. However, it models the sparseness of nonzero similarities of a patch with its neighboring patches instead of high-frequency features. The patch sparse representation is inspired by the recent progress on sparse representation, which assumes that the image or signal is represented by the sparse linear combination of an over-complete library of bases or transforms under sparseness regularization. This framework has been widely applied to image denoising, edge detection, recognition, super-resolution, texture synthesis, etc., and achieved state-of-the-art performance. In this work, the idea of sparse representation is introduced to the examplar-based inpainting algorithm under the assumption that the missing patch can be represented by the sparse linear combination of candidate patches. Then a novel constrained optimization model is designed for patch inpainting.

IV. PROPOSED WORK

A. *Algorithm Overview*

Given an image I with the missing region Ω and the known region $\overline{\Omega}$, the task of image inpainting is to fill in the target region (i.e., the missing region Ω) using the image information in the source region (i.e., the known region $\overline{\Omega}$). The boundary of the target region is denoted by $\partial\Omega$, which is called the fill-front in the examplar-based inpainting algorithm. We further denote as Ψ_p a patch centered at a pixel p.

The main procedures of the proposed examplar-based inpainting algorithm are illustrated in Fig. 1. This algorithm is based on patch propagation by inwardly propagating the image patches from the source region into the interior of the target region patch by patch. In each iteration of patch propagation, the algorithm is decomposed into two procedures: patch selection and patch inpainting.



(a) Patch Selection (b) Patch Inpainting

Fig.1. Image inpainting using patch sparsity. Ω is the missing region, $\overline{\Omega}$ is the known region, and $\partial\Omega$ is the fill-front of patch propagation. Iterate the following two steps until completion. (a)

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Patch selection: The patch Ψ_p on the fill-front with the larger sparseness of nonzero similarities to its neighboring patches is encouraged to be selected with higher priority. The top left of (a) shows two examples of known image parts surrounding patch Ψ_p and $\Psi_{p'}$, which locate at edge and flat texture region respectively. The bottom-left of (a) shows the similarities of Ψ_p and $\Psi_{p'}$ with their surrounding known patches, the higher brightness means larger similarity. Obviously, similarity map of Ψ_p is much sparser than that of $\Psi_{p'}$. (b) Patch inpainting: For the selected patch $\Psi_{p'}$, sparse linear combination of candidate patches $\Psi_{q^1}, \Psi_{q^2}, \ldots\ldots \Psi_{q^n}$ is used to infer the missing pixels in patch Ψ_p under the constraint of local patch consistency in $N(p) \cap \overline{\Omega}$.

In the procedure of patch selection, patch priority should be defined to encourage the filling-in of patches on the structure with higher priority. We define **structure sparsity** by measuring the sparseness of the similarities of a patch with its neighboring patches. Then patch priority is defined using the structure sparsity. In the example shown in Fig. 1(a), the patches Ψ_p and $\Psi_{p'}$ are centered at pixel and which lie in the edge structure and the flat texture region respectively. The left-down part of Fig. 1(a) shows the maps of their similarities with neighboring known patches. Obviously, the patch has sparser nonzero similarities; therefore, it has larger patch priority. The patch on the fill-front with the highest priority is selected to be inpainted firstly.

In the procedure of patch inpainting, the selected patch on the fill-front should be filled in. Instead of using a single best match examplar or a certain number of examplars in the known region to infer the missing patch.

B. Patch Priority Using Structure Sparsity

The natural images are generally composed of structures and textures. A good definition of patch priority should be able to better distinguish the structures and textures, and also be robust to the orientation of the fill-front. In this paper, a novel definition of patch priority is proposed to meet these requirements. We now introduce the key component of our definition of patch priority, i.e., structure sparsity.

1) Structure Sparsity: The structure sparsity is defined to measure the confidence of a patch located at structure instead of texture. Structure sparsity is inspired by the following observations:

Structures are sparsely distributed in the image domain, e.g., the edges and corners are distributed as 1-D curves or 0-D points in the 2-D image domain. Nevertheless, the textures are distributed in 2-D sub-regions of the image domain, which are less sparsely distributed. On the other hand, for a certain patch, its neighboring patches with larger similarities are also distributed in the same structure or texture as the patch of interest. Therefore, we can model the confidence of structure for a patch by measuring the sparseness of its nonzero similarities to the neighboring patches. The patch with more sparsely distributed nonzero similarities is prone to be located at structure due to the high sparseness of structures.

Suppose Ψ_p is a patch on the fill-front $\partial\Omega$ its neighboring patch Ψ_{pj} is defined as the patch that is in the known region and with the center pj in the neighborhood of pixel p, i.e. pj, belongs to the set

$$N_s(p) = \{p_j : p_j \in N(p) and \Psi_{pj} \subset \overline{\Omega}\} \qquad (1)$$

$N_{(P)}$ is a neighborhood window centered at p, which is set to be larger than the size of patch Ψ_p Suppose p is a matrix to extract the missing pixels of Ψ_{pj}, and $\overline{p}$ extracts the already known pixels of Ψ_p, then the similarity between Ψ_p and Ψ_{pj} is defined as

$$\omega_{p,\,pj} = \frac{1}{z(p)} \exp\left(- \frac{d\left(\overline{P}\Psi_P, \overline{P}\Psi_{pj}\right)}{\sigma^2} \right) \qquad (2)$$

Where $d(.,.)$ measures the mean squared distance $z(p)$, is a normalization constant such that $\sum_{pj \in N_S(P)} \omega_{p,pj} = 1$ and σ is set to 5.0 in our implementation. For the patch Ψ_p, we measure the sparseness of its similarities to the neighboring patches in region $N_S(p)$ by

$$\rho(p) = \|\vec{\omega}_p\|_{L_2} \sqrt{\frac{|N_S(p)|}{|N(p)|}} = \sqrt{\left[\sum_{pj \in N_S(p)} \omega^2_{p,pj}\right]} \cdot \frac{|N_S(p)|}{|N(p)|} \qquad (3)$$

Where $\vec{\omega}_p$ is the vector of elements $\omega_{p,pj}\left(p_j \in N_S(p)\right)$, and $[\cdot]$ Means the number of elements. $|N_{(P)}|$ is incorporated to restrict $\rho(p)$ in the interval $(0,1]$, though its value is same for different patches. This definition embodies the fact that the larger sum of squared similarities in the larger region N_s means larger sparseness. The structure sparsity achieves its maximum and Minimum Values When The Patch Similarities Are Distributed in the sparsest and smoothest fashion respectively, and the structure sparsity increases with respect to the sparseness of patch's nonzero similarities to its neighboring patches.

C. Patch Priority

The final patch priority is defined by multiplying the transformed structure sparsity term with patch confidence term: $P(p) = T_{[\zeta,1]}(\rho(p)) \cdot C(p) \cdot C(p)$ is the confidence of patch Ψ_p which specifies the reliability of color or intensity in the patch. It is same as,

$$C(p) = \sum_{q \in \Psi(p) \cap \overline{\Omega}} c(q) / |\Psi(p)|,$$

Where, $c(q)$ is the confidence of the color or intensity of pixel q, and initialized to 0 in the missing region or 1 in the known region. After each procedure of patch inpainting, the confidences of the newly filled

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pixels in the patch are updated by the confidence of the patch's central pixel. $T_{[\zeta,1]}$ is a linear transformation of $\rho(p)$ from its original interval to the interval $[\zeta,1]$.

$$\left[\sqrt{1/|N(p)|}, \sqrt{|N_s(p)|/|N_s(p)|}\right]$$

Where, ζ is set to 0.2. This transformation is necessary to make the structure sparsity varies in a comparable scale with $C(p)$ By multiplying these two terms in with $P(p)$ the inpainting algorithm is encouraged to firstly inpaint the patch located at image structures (i.e., edges or corners) and with larger confidence of its colors or intensities, then the missing region with composite texture and structure can be more robustly inpainted.

D. Patch Sparse Representation

The patch Ψ_p on the fill-front with the highest patch priority is selected to be filled firstly. In the traditional examplar-based inpainting technique Ψ_p is filled by sampling the best match patch from the known region. Recently, a nonlocal means approach is proposed to fill in patch by the nonlocal means of several top similar patches instead of a single best match patch. Due to multiple samples are utilized, it can more robustly estimate the missing information and produce better result. However, it tends to introduce smooth effect in the recovered image. In this work, we propose a novel model to inpaint patch by the sparse combination of multiple examplars in the framework of sparse representation. This method achieves sharp inpainting result by sparseness prior on the combination coefficients, and achieves consistent inpainting results with the surrounding textures by the constraints on the patch appearance in local neighborhood.

E. Optimization Algorithm

Generally, the ℓ^0-norm regularized reconstruction model is hard to be solved due to its combinatorial nature. Matching pursuit (MP) or orthogonal matching pursuit (OMP) algorithm and basis pursuit (BP) algorithm can efficiently retrieve the sparse representation and approximate the optimal solution in a greedy fashion. Another method for optimizing the ℓ^0-norm regularized model is to convexify the problem by ℓ^1 -norm regularization. The ℓ^1 -norm regularized reconstruction model is the well-known Lasso in the statistical literatures. In applications, due to the simplicity of OMP algorithm, it is widely used in image sparse representation, and applied to image denoising, coding, edge detection, audio source separation, and so on.

For this optimization problem, we propose a novel algorithm to derive the sparse linear combination coefficients in a greedy fashion.

V. ADVANTAGES

- The exemplar based approach is used removing *large* objects from digital photographs.
- The technique is capable of propagating both linear structure and two-dimensional texture into the target region with a single, simple algorithm.
- Structure sparsity enables better discrimination of structure and texture.
- The patch sparse representation forces the newly inpainted regions to be sharp and consistent with the surrounding textures.
- Also, patch-based filling helps achieve:
  (i) Speed efficiency
  (ii) Accuracy in the synthesis of texture (less garbage growing).
  (iii) Accurate propagation of linear structures.

VI. CONCLUSION

This paper proposed novel patch propagation based inpainting algorithm to be implemented in MATLAB for scratch or text removal, object removal and missing block completion. The major novelty of this work is that two types of patch sparsity were proposed and introduced into the examplar-based inpainting algorithm. This was inspired from the recent progress of the research in the fields of image sparse representation and natural image statistics.

Structure sparsity was designed by measuring the sparseness of the patch similarities in the local neighborhood. The patch with larger structure sparsity, which is generally located at the structure, tends to be selected for further inpainting with higher priority. On the other hand, the patch sparse representation was proposed to synthesize the selected patch by the sparsest linear combination of candidate patches under the local consistency constraint.

We test the proposed examplar-based patch propagation algorithm on a variety of natural images. We apply our algorithm to the applications of scratch/text removal, object removal and block completion. We compare our algorithm with the previous diffusion-based, examplar-based, and sparsity-based inpainting algorithms. With the help of Comparisons, we will show that the proposed examplar-based patch propagation algorithm can better infer the structures and textures of the missing region, and produce sharp inpainting results consistent with the surrounding textures.

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AUTHOR PROFILE

Pranali Dhabekar, Rreceived the degree of B.E in Electronics and Telecommunication Engineering from Terna Engineering College, Osmanabad, Maharashtra in 2007 and persuing M.E. in Electronics & Telecommunication Engineering from Genba Sopanrao Moze College of Engineering, Balewadi, Pune. With having 4 years teaching experience. Her research interest include image processing which is applied in this work.

Geeta Salunke, M. E. in Electronics, is assistant professor in the department of Electronics and Telecommunication Engineering at Genba Sopanrao Moze college of Engineering. With over 13 years of experience, she has published papers in national conference. Her main areas of interest include Image Processing and Communication System.

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