Image Inpainting Using Patch Sparsity Approaches

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***Abstract*—In this paper we discuss a modified exemplar-based inpainting method through investigating the sparsity of natural image patches. In the exemplar-based algorithms, with the help of available information the unknown blocks of target region are inpainted by the most similar blocks extracted from the source region. To decide the filling order of missing pixels ensures the connectivity of object boundaries. The priority term shold defined. We discuss modification of the priority term and take measures to compute the similarities between fill-front and candidate patches. Image inpainting by patch propogation using patch sparsity shows the effeteness over traditional exemplar based inpainting. In this paper we have studied and reviewed different algorithms implemented in the past for performing Image Inpainting. We have classified some algorithms for Image Inpainting.**

***Keywords*—Image inpainting, texture synthesis, patch sparsity, patch propagation, sparse representation.**

I. INTRODUCTION

THE Reconstructing of missing region in an image, which is called image inpainting, is an important topic in the field of image processing. Applications of image inpainting include old film restoration, video inpainting [1], de-interlacing of video sequences [2], and cloud removal from remotely sensed images [3]. Many successful algorithms for image inpainting have been developed in the past decade. The most fundamental in painting 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. Within the category of PDE-based methods, there are a number of approaches which perform well for piecewise smooth images with sharp edges. These algorithms are well founded on the theory of partial differential equation (PDE) and variation method. Bertalmio*et al.* [4] filled in holes by continuously propagating the isophote (i.e., lines of equal gray values) into the missing region. They further introduced the Navier–Strokes equation in fluid dynamics into the task of inpainting [5] Other PDE-based algorithms [6] were proposed by Chan and Shen. The Total Variational (TV) model [7] uses an Euler-Lagrange equation coupled with anisotropic diffusion to preserve the direction of isophotes. This method does not restore a single object well when its disconnected remaining elements are separated far apart within the target region. The Curvature Driven Diffusion (CDD) model [7] considers geometric information by defining the strength of isophotes. This extended version of TV algorithm can inpaint larger damaged regions. 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, texture synthesis techniques, were proposed. The common idea in these methods is to duplicate the information for the source region into the target region helps to fill large regions with pure textures hence, the texture information is preserved. Texture synthesis approaches are classified into pixel based sampling and patch-based sampling according to the sample texture size. Since the filling process in pixel-based schemes is being performed pixel by pixel, the algorithms are very slow. Although the speed of patch-based sampling was greatly improved, in which the target region is filled in by blocks of pixels, but discontinuous flaws between neighboring patches still remains.

Third category of approaches is the exemplar-based in painting 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. 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*et al.* [8] 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. Which overcomes the smooth effect of the diffusion-based inpainting algorithm; however, it is still hard to recover larger missing structures. Criminisi*et al.* [9] designed an examplar-based inpainting algorithm by propagatingthe known patches into the missingpatches gradually. To handle the missing region with compositetextures and structures, patch priority is defined to encouragethe filling-in of patches on the structure. Wu [10] proposed across-isophotes exemplar-based inpainting algorithm, in whicha cross-isophotes patch priority term was designed based onthe analysis of anisotropic diffusion. Wong [11] proposed anonlocal means approach for the exemplar-based inpaintingalgorithm. The image patch is inferred by the nonlocal meansof a set of candidate patches in the known region instead ofa single best match patch. theexemplar-based inpainting algorithms have performed plausibleresults for inpainting the large missing region.

Recent approaches based on image sparse representation have also been introduced for the inpainting problem [12-15]. In these methods, an image is presented by a sparse combination of an over complete set of transformations (e.g., wavelet, contourlet, DCT, etc.), and then the missing pixels are inferred by adaptively updating the sparse representation. Elad et al[12], proposed an approach to separate the image into cartoon (structure) and texture components, and then represented the sparse combination of the two obtained components by two incoherent over-complete transformations. This approach can effectively fill in the regions with structure and texture, it may fail to repair the structure or might produce smoothing. A sparse representation-based iterative algorithm for image inpainting proposed by Fadili et al [13]. They used the Expectation Maximization (EM) framework to consider that the missing samples can be recovered based on representations. Xu and Sun [14] suggested an exemplar-based inpainting method using a patch sparsity representation. They introduced the idea of sparse representation under the assumption that the missing patch could be represented by sparse linear combinations of candidate patches. Then, a constrained optimization model was proposed for the patch inpainting. Nonetheless, the edges in the filled regions sometimes are not connected properly. Hesabi and amir [15] proposed a modified patch propogation based image inpainting they define new priority term for sparse representation of missing pixel.

In this paper we will study in details about patch based algorithms proposed by Criminisi et al [15], exemplar-based inpainting method using a patch sparsity representation Xu and Sun [14] and modified patch propogation based image inpainting. Hesabi and amir [15].] Here we discuss a modified patch propogation based image inpaintingalgoritham.

The remainder of our work is organized as follows. In Section 2, we explain the patch sparsity-based image inpainting. We present our proposed method of our technique in Section 3. Section 4 gives the concluding remarks. Finally, Section 5 we discuss about future work.

II. PATCH SPARSITY BASED INPAINTING

The two important term in an patch selection and patch inpainting, two novel concepts of patch sparsity of natural image, i.e., patch structure sparsity and patch sparse representation, are proposed and applied to the examplar-based inpainting algorithm. First, we define a novel patch priority based on the sparseness (***structuresparsity)*** of the patch's nonzero similarities to its neighboring patches.

Another, 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. the structure sparsity and patch sparse representation at the patch level constitute the ***patch sparsity***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 *lp*(0< p< 2) sparseness regularization.

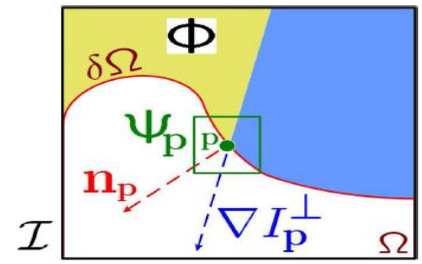

Fig. 1 Notation diagram

Given an image I with the missing region Ω and the known Region Ω', the task of image inpainting is to fill in the target Region using the image information in the source region δΩ . The boundary of the target region is denoted byΨp , which is called the fill-front in the examplar-based inpainting algorithm. We further denote as a patch centered at a pixel .

Algorithm 1: *Exemplar base Image Inpainting*

Step 1: For each point pon the boundary δΩ, a patch $\Psi p$is constructed, with pin the center of the patch.

Step 2: A new definition for patch priority, *structure sparsity*, is proposed. For any selected patch, a collection of neighboring patches with highestsimilarities are also distributed in the same structure or texture. Therefore, the confidence ofstructure for a patch is measured by the sparseness of its nonzero similarities to the neighboringpatches. The patch with more sparsely distributed nonzero similarities is laid on the fill-front due tothe high structure sparseness. For the patch , located at the fill-front δΩ, a neighborhood window N(p), with the center p,is set. The sparseness of similarities for the patch is measured by

$$P(p) = \sqrt{[\sum_{Pj \in Ns(p)} W^2 \text{ p, pj}] - 4ac]\frac{|Ns(p)|}{|N(p)|}} \quad (1)$$

where, the patch $\Psi p, pj$is located in the known region centered at $Pj. Wp, pj$ belongs to the similarity between $\Psi p$and Ψpj, defined as:

$$Wp, pj = \frac{1}{Z(p)} \exp(-\frac{(d\Psi p\ ,\Psi j)}{\sigma^2}) \quad (2)$$

withdmeasuring the mean squared distance of the already known pixels in the two patches, Z(p)being a normalization constant so that

$\sum_{Pj \in Ns(p)} W^1$ p, pj=1, and σ being set to 5. Finally, Ns(p) belongs to the set of thePj, that is,

Ns(p) =[Pj:Pj∈N(p)and Ψp ∈⊂ Ω′] (3)

The patch priority (or structure sparsity) term is defined as the product of the transformed structure sparsity term and the patch confidence term:

P(p)= $T_{[\xi,1]}\big(P(p)\big).C(p)$, (4)

where, $T_{[\xi,1]}$is a linear transformation taking P(p)into the interval$[\xi, 1]$. This transformation scalesthe structure sparsity variations to be comparablewith C(p).

Step 3: The patch $\Psi p'$with the highest priority is found to be filled in with the information extracted from the source region φ.

Step 4: In the patch sparsityinpainting method,Ψp is inpainted by the sparse combinations of multiple examplars in the framework of sparse representation. from the source region, the top Nmost similar patches, as the set of candidates ,$\Psi q_{q=1}^{N}$ are selected.Therefore, the unknown pixels in patch $\Psi p$is approximated by linear combinations of the$\Psi q_{q=1}^{N}$ie.

$\Psi q' = \sum_{q}^{N} \alpha_q \Psi q$ (5)

where, the coefficient $\bar{\alpha} = \{\alpha_1, \alpha_{2,}\alpha_3, \dots \alpha_N\}$is obtained by solving a constrained optimization problem in the framework of a sparse representation. This optimization problem minimizes the *l0* norm of $\bar{\alpha}$, i.e., the number of nonzero elements in the vector $\bar{\alpha}$, with the linearity assumption of the combination.

Step 5: The value of each pixel to be filled in, P'|p$'\epsilon(\Psi p \cap$ Ω, is copied from its corresponding position inside Ψq.

Step 6: The confidence term C(p)is updated in the area encircled by Ψpas follows:

C(q) = C(p'), ∀q∈$(\Psi p \cap \Omega)$ (6)

The method investigates the sparsity of image patches, and measures the confidence of the patch located at the structure region by the sparseness of its nonzero similarities to the neighbouring patches. The patch with larger structure sparsity is assigned a higher priority for further inpaintings.

III. MODIFIED METHOD

We modify steps 2, 4 and 6 to attain better results

Algorithm 2: *A modified patch propagation-based image inpainting using patch sparsity*

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Step 1: For each point pon the boundary δΩ, a patch $\Psi p$is constructed, with pin the center of the patch.

Step 2: To compute the patch's priority P(p), a stable definition is used:

P(p)= $\alpha T_{[\xi,1]}\big(P(p)\big) + T_{[\gamma,1]}$(C(p)) (7)

where, the terms $\alpha T_{[\xi,1]}\big(P(p)\big)$and C(p) are the same as the ones defined in [14], andα and βare the component weights with 0 ≤α, β≤1 and α+β=1. As illustrated in [20], the confidence value rapidly drops to zero as the filling process goes on. When the dropping effect occurs, error continually propagates to the central part of the reconstructed image, causing noticeable visual artefacts. Therefore, a regularizing transformation is used to control the decreasing rate of the confidence term. In our experiments, we use a linear transformation T'to take C(p) into the interval [γ,1]. Also, the priority term is changed to an additive form instead of a multiplicative form (because the numerical multiplication is effectively sensitive to extreme values, while the additive has shown more robustness relative to its inputs and so it is more stable).

A global search is carried out image to find a patch Ψqth similarity with $\Psi q'$ in step 4 similar to the algoritham 1.

Step 3: The patch $\Psi p'$with the highest priority is found to be filled in with the information extracted from the source region φ.

Step 4:A global search is carried out on the whole image to find a patch Ψqthat has the most similarity with $\Psi p'$. Formally,

$\Psi q'$ = arg minϵφ$d(\Psi p', \Psi q)$ (8)

where, the distance *d* between two generic patches is simply defined as the sum of squared differences (SSDs) of the already known pixels in the two patches.

Step 5: The value of each pixel to be filled in, P'|p$'\epsilon(\Psi p \cap$ Ω, is copied from its corresponding position inside Ψq.

Step 6: Let $\Psi q' = \sum_{q=1}^{N} \alpha_q \Psi q$

Denote the unknown pixels in the patch Ψp', by a matrix P, filled by the corresponding pixels inΨq':

$$P\Psi p' = P\Psi q'.$$

the coefficients $\bar{\alpha} = \{\alpha_1, \alpha_{2,}\alpha_3, \dots \alpha_N\}$ are obtained by solving the following constrained optimization problem:

min$\|\bar{\alpha}\|$o

s.t.$\|P\Psi p' = P\Psi q'\|^2 < \xi$,

$$\beta \left\| P\Psi q' - P \sum_{pj \in Ns(p)} Wp,pj\Psi pj \right\|^2 < \xi,$$

$$\sum_{i}^{N} \alpha = 1$$

The first and the second constraints concern the local patch consistency. The first constraint constrains the estimated patch Ψq' approximated by the target patch Ψp' over the already known pixels, and the second one forms the consistency between the newly filled pixels and the neighboring patches in appearance. It measures the similarity between the estimated patch and the weighted mean of the neighboring patches over the missing pixels. The last constraint imposes a normalization summation on the coefficients vector α. This constraint is used to achieve invariancy while reconstructing the target patch from its neighboring candidate patches. The parameter ξ is to control the error tolerance, β balances the strength of the two first constraints, which is set to 0.25 in our implementation.The local patch consistency constraint can be rewritten in a compact form:

$$\|D\Psi q - \Psi t\|^2 < \xi,$$

$$D = [{}^{\bar{P}}_{P\sqrt{\beta}}],$$

$$\Psi t = \begin{bmatrix} P\Psi p' \\ \sqrt{\beta}P\sum_{Pj\in N(S)} Wp,pj\Psi pj \end{bmatrix}$$

So, the optimization problem can be formulated as

$$\min\|\bar{\alpha}\|o$$

$$s,t,\|D\Psi q - \Psi t\|^2 < \xi$$

$$\sum_{i}^{N}\alpha = 1$$

Which can be solved in the same way as in Locally linear embedding (LLE) for data deduction.

Step 7: The confidence term C(p) is updated the area encircled by $\Psi p'$ as follow

C(q) = $C(\mathrm{p}')\frac{|\{q|q\in(\Psi p'\cap\Omega')\}|}{|\Psi p'|}$∀q$\in(\Psi p'\cap\Omega)$

where, the numerator in the first term is number of known pixel in the patch $\Psi p'$.

CONCLUSION

In this paper, we have looked at two different types of inpainting methods. For each of the algorithms, we have reviewed and provided a detailed explanation of the process used for filling an obstruction making use of images and pseudo-code wherever appropriate. In addition, we have updated confidence value in adaptive way in both a qualitative and quantitative manner. From this analysis, a number of shortcomings and limitations were highlighted in relation to the type of information each algorithm can restore.

In a modified patch sparsity scheme for inpainting degraded images. Addressing the patch sparsity approach as a robust inpainting method, the suggested modifications lead to an improvement in producing better results. We applied the proposed algorithm to several images and compared the obtained result with those obtained by three other methods. The high visual quality of the results obtained by our approach affirmed the effectiveness of the modified algorithm.

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