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Multiple Examplar-Based Inpainting

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***Abstract*--. Image Inpainting is a new area of research in the field of image processing which has gained wide popularity because of its large number of applications. Image inpainting technique has been widely used for reconstructing damaged old photographs and removing unwanted objects from images. The proposed multiple examplar-based method follows the two classical steps the filling order computation and the texture synthesis. The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. Classically, a high priority indicates the presence of structure. The priority of a patch is just given by a data and confidence term.**

In this paper we used the data term, a tensor-based and a sparsity-based data terms.

***Keywords*— Object Removal, Image Inpainting, Texture Synthesis, Simultaneous ,Texture and Structure Propagation.**

I. INTRODUCTION

In the world of image processing "Filling the Missing Areas (holes)" is a problem in several image processing applications [1]. Even though so much research has done in this area, still it's an area of concern in many digital image processing applications. Image inpainting is the approach of reconstructing lost or manipulated parts of images. Existing methods are broadly classified into two sections a) Diffusion based approach b) Examplar based approach. These two existing methods are inspired from the texture synthesis techniques [2].Diffusion based approach generates the isophotes via diffusion based on variational structure or variational method [3], the main drawback of diffusion based approach is have a tendency to introduce some blur when the filling the missing area is very large. Latter method of approach is Examplar based approach which is quite simple and innovative, in this method copy the best sample from known image neighborhood. Initially examplar method approach is implemented on object removal as chronicled in [4], searching the alike patches is done by using the priori rough estimate method of the inpainted image values utilizing the multi-scale approach.

In order to yield the better result, both diffusion based approach and Examplar based approach are then efficiently combined. For example by utilizing the structure tensor to calculate the priority of the patches to be filled, based on this priority filling is done as explained in [5].

Although lot of advancement done in the past decade on examplar based inpainting still lot problems to be addressed in all the main area of concern is patch size and filling the holes related to settings configuration. This problem is here addressed by several input inpainting versions to yield the final inpainting image after combining the all input inpainting versions.

II. PROPOSED APPROACH

A. Multiple Exemplar-Based Inpainting

This section aims at presenting the proposed Inpainting method and the combination of the different inpainted images.

B. Exemplar-Based Inpainting

The proposed examplar-based method follows the two classical steps as described in the filling order computation and the texture synthesis. These are described in the next sections.

Patch Priority

The filling order computation defines a measure of priority for each patch in order to distinguish the structures from the textures. Classically, a high priority indicates the presence of structure. The priority of a patch centered on *p***x** is just given by a data and confidence term. The latter is exactly the one defined in [4]. Regarding the data term, a tensor-based [6] and a Sparsity-based [9] data terms have been used. These terms are briefly described below. The tensor-based priority term is based on a structure tensor also called Di Zenzo matrix [10]; this is given by

$$J = \sum_{i=1}^{m} \nabla I_i \nabla I_i^T \qquad (1)$$

J is the sum of the scalar structure tensors $\nabla I_i \nabla I_i^T$ ofeach image channel *Ii* (R,G,B). The tensor can be smoothed without cancellation effects: $J\sigma = J * G\sigma$ Where $G_\sigma = {}^{1}/_{2\pi\sigma^2} \exp\left(-{}^{(x^2+y^2)}/_{2\sigma^2}\right)$ with standard deviation σ. One of the main advantages of a structure tensor is that a structure coherence indicator can be deduced from its eigenvalues. Based on the discrepancy of the eigenvalues, the degree of an isotropy of a local region can be evaluated. The local vector geometry is computed from the structure tensor **J***σ*. Its eigenvectors $\mathbf{v}_1$, $\mathbf{v}_2$ ($\mathbf{v}_i \in R^n$) define an oriented orthogonal basis and its eigenvalues $\lambda_{1,2}$ define the amount of structure variation. The vector $\mathbf{v}_1$ is the orientation with the highest fluctuations (orthogonal to the image contours), whereas $\mathbf{v}_2$ gives the preferred local orientation. This eigenvector (having the smallest eigenvalue) indicates the isophote orientation. A data term D is then defined as [11]:

$$D(P_x) = \alpha + (1\alpha)\ \exp\left(-\frac{\eta}{(\lambda_1-\lambda_2)^2}\right) \quad (2)$$

where η is a positive value and $\alpha \in [0, 1]$ ($\eta = 8$ and $\alpha = 0.01$). On flat regions ($\lambda_1 \approx \lambda_2$), any direction is favoured for the propagation (isotropic filling order). When $\lambda_1 >> \lambda_2$ indicating the presence of a structure, the data term is important.

The Sparsity-based priority has been proposed recently by Xu et al. [9]. In a search window, a template matching is performed between the current patch ψ_{px} and neighbouring patches ψ_{pj} that belong to the known part of the image. By using a non-local means approach [8], a similarity weight $w_{p_x,\ p_j}$ (i.e. proportional to the similarity between the two patches centered on p_x and p_j) is computed for each pair of patches. The Sparsity term is defined as:

$$D(p_x) = \| w_{p_x} \|_2 \times \sqrt{\frac{|N_s(p_x)|}{|N(p_x)|}} \quad (3)$$

where Ns and N represent the number of valid patches (having all its pixels known) and the total number of candidates in the search window. When $\| w_{p_x} \|_2$ is high, it means larger sparseness whereas a small value indicates that the current input patch is highly predictable by many candidates.

Texture Synthesis

The filling process starts with the patch having the highest priority. To fill in the nknown part of the current patch ψ_{px}^{uk} the most similar patch located in a local neighbourhood w centered on the current patch is sought. A similarity metric is used for this purpose. The chosen patch ψ_{px}^{*} maximizes the similarity between the known pixel valuesof the current patch to be filled in ψ_{px}^{k} and co-located pixel values of patches belonging to W:

$$\psi_{px}^{*} = \arg\ \min d\left(\psi_{px}^{k}, \psi_{pj}^{k}\right)$$

$$\text{s.t.} \quad Coh(\psi_{px}^{uk}) < \lambda_{coh} \quad (4)$$

where d(.) is the weighted Bhattacharya used in [7].Coh(.)is the coherence measure initially proposed by Wexler et al.[8]

$$Coh\left(\psi_{px}^{uk}\right) = \min\left(d_{SSD}\left(\psi_{px}^{k}, \psi_{pj}^{k}\right)\right) \quad (5)$$

where dSSD is the sum of square differences. The coherence measure Coh simply indicates the degree of similarity between the synthesized patch ψ_{px}^{uk} and original patches.

Compared to previous work [7], there is another substantial difference we only use the best match to fill in the hole whereas a linear combination of the K most similar patches is generally performed to compute the patch in [7], [8], [9], [12]. In these cases, the estimated patch is then given by:

$$\psi_{px}^{*} = \sum W_{p_x,p_j} \times \psi_j^k \quad (6)$$

Where K is the number of candidates which is often adapted locally so that the similarity of chosen neighbours lies within a range (1+α) × dmin, where dmin is the distance between the current patch and its closest neighbours. Different methods can be used to compute the weights. It could be based on either anon-negative matrix factorization (NMF) [13] or a non local means filter [8], [14], to name a few. Combining several candidates increases the algorithm robustness. However, it tends to introduce blur on fine textures as illustrated by Fig. 1In our method, only the best candidate is chosen. Its unknown parts are pasted into the missing areas. A Poisson fusion [15] is applied to hide the seams between known and unknown parts.

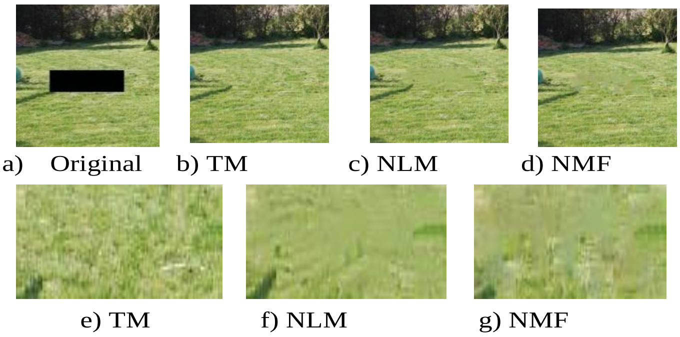

Fig.1.(a)Original Picture with a Black Hole to be Filled in,(b) Result Obtained with a Simple Template matching (TM), with the Linear Combination of the K Most Similar Neighbors in which Weights are Computed by Using a Non Local Means Method (c),and by a Non Negative Matrix Factorization (d). for this Example, the Maximum Number of Neighbors is 10. (e)-(g) Zoom in the Inpainted Part for TM, NLM, and NMF, respectively.

Although the proposed method is able to fill in holes in a visually pleasant fashion (as illustrated by Fig.1),it still suffers from problems of one-pass greedy algorithms. Indeed for most of existing approaches, the setting such as the patch size and the filling order, to name the most important factors, may dramatically impact the quality of results. To overcome this issue, we combine inpainted pictures obtained when different settings are used. In this study, we consider M = 13, meaning that the low-resolution picture is inpainted 13 times. Parameters are given in Table I: the patch size is chosen between 5 × 5, 7 ×

7, 9 × 9 and 11 × 11. The filling order is computed by either the Sparsity-based or the tensor-based method. The input picture can also be rotated by180 degrees. This allows changing the filling order

C. Combining Multiple Inpainted Images

The combination aims at producing a final inpainted picture from the M inpainted pictures. Before delving into this subject in details, Fig. 2 illustrates some inpainted results obtained for a given setting. We notice again that the setting plays an important role. To obtain the final inpainted picture, three kinds of combination have been considered. The first two methods are very simple since every pixel value in the final picture is achieved by either the average or the median operator as given below

$$\hat{I}^{(*)}(P_X) = \frac{1}{M}\sum_{i=1}^{M} \hat{I}^{(i)}(P_X) \qquad (7)$$

$$\hat{I}^{(*)}(P_X) = \mathrm{MED}_{i=1}^{M}\hat{I}^{(i)}(P_X) \qquad (8)$$

The advantage of these operators is their simplicity. However they suffer from at least two main drawbacks. The average operator as well as the median one do not consider the neighbors of the current pixel to take a decision. Results might be more spatially coherent by considering the local neighborhood. In addition, the average operator inevitably introduces blur as illustrated by Fig. 3.To cope with these problems, namely blur and spatial consistency of the final result, the combination is achieved by minimizing an objective function. Rather than using a global minimization that would solve exactly the problem, we use a Loopy Belief Propagation which in practice provides a good approximation of the problem to be solved. This approach is described in the next section.

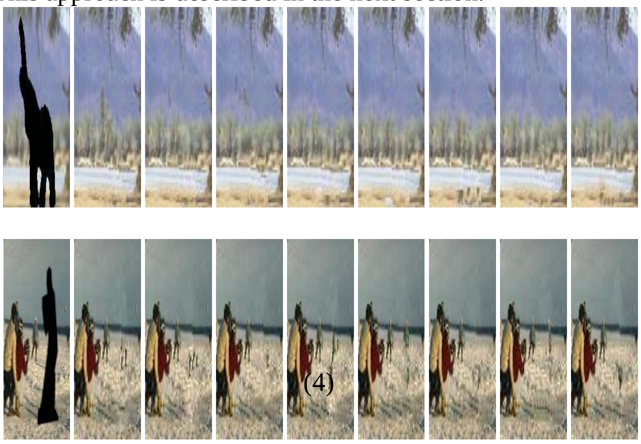

Fig 2 MaskS1 S2 S3 S4 S5 S6 S7 S8

Loopy Belief Propagation

LBP is a message passing algorithm. A node is used to pass a message to the adjacent node only when it has received all the messages, eliminating the message from the destination node to itself. In the same way, all the inpainted images are combined together using loopy belief propagation. A label is assigned to each pixel of the unknown regions T of the image. A major drawback of belief propagation is that it is slow when the number of labels is high. So loopy belief propagation is used to avoid this complexity. To solve the problems like blur and spatial consistency, there is a need to minimize the objective function. The number of labels assigned must be equal to the number of patches in the source region. In loopy belief propagation, the number of labels is small. Label is the index of the inpainted image from which the patches are extracted. A label is assigned for each pixel so that the total energy E of the markov random field is minimized.

The cost increases when the similarity between the current patch and collocated patches are less. Discontinuity cost is the difference between labels. λ is the weighing factor and it is set to 100.Using loopy belief propagation, minimization of energy E is performed over the target region T and it corresponds to maximum a posteriori (MAP) estimation problem. When λ is 0, there is no smoothness term. Some artifacts are visible. A good trade-off is obtained by setting the value of λ to100.

As in [16], the problem is to assign a label to each pixel p**x** of the unknown regions T of the picture $\hat{\mathbf{I}}(*)$ The major drawback of the belief propagation is that it is slow especially when the number of labels is high .Komodakis and Tziritas [16] have designed a priority Belief Propagation in order to deal with this complexity bottleneck. Indeed, the number of labels in [16] is equal to the number of patches in the source region. Here the approach is simpler since the number of labels is rather small; a label is simply the index of the inpainted picture from which the patch is extracted. A finite set of labels L is then composed of M values (M = 13 here), going from 1 to M. This problem can be formalized with a Markov Random Field (MRF) G = (ν , ∊) defined over the target region T . The MRF nodes ν are the lattice composed of pixels inside T .Edges are the four connected image grid graph centered around each node. We denote N4 this neighbourhood system. The labeling assigns a label ℓ ($\ell \in \mathcal{L}$) to each node/pixel P**x** (p**x** ϵ T) so that the total energy E of the MRF is minimized (we denote by ℓp the label of pixel p**x**) [17], [18]:

$$E(l) = \sum_{p\in v} V_d(l_P) + \sum_{(n,m)\in N_4} V_S(l_n, l_m) \qquad (9)$$

vd (lp) is the label cost Vs (ln , lm) is the discontinuity cost

Fig.3 Comparison of Combination Methods.(a)Input Picture,(b) Results Obtained by Averaging all Inpainted Pictures,(C) by Taking the Median Pixel Values, and (D)by Using a Loopy Belief Propagation.

III. CONCLUSION

Exemplar-based image inpainting gives better results as compare to PDE-based image inpainting. The performance of the exemplar-based image inpainting can be improved by using different parameter setting and combining image with Loopy Belief Propagation. The structure and texture information are used to determine appropriate patch size and candidate source region. With this approach, we can reduce the number of iterations and error propagation caused by incorrect matching of source The filling order is computed by either the sparsity-based or the tensor-based method. The input picture can also be rotated by 180 degrees. This allows changing the filling order..

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