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Object Elimination and Reconstruction Using an Effective Inpainting Method

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Abstract: *Three major problems have been found in the existing algorithms of image inpainting: Reconstruction of large regions, Preference of filling-in and Choice of best exemplars to synthesize the missing region. The proposed algorithm introduces two ideas that deal with these problems preserving edge continuity along with decrease in error propagation. The proposed algorithm introduces a modified priority computation in order to generate better edges in the omitted region and to reduce the transmission of errors in the resultant image a novel way to find optimal exemplar has been proposed. This proposal optimizes the reconstruction process and increases the accuracy. The proposed algorithm removes blurness and builds edges efficiently while reconstructing large target region.*
Keywords: *Image inpainting, texture synthesis, Image Completion, exemplar-based method.*

I. Introduction

Image inpainting techniques are used to remove scratches in photographs, repairing damaged regions in paintings and removing unwanted objects in an image. The challenge of present inpainting algorithms is to reconstruct texture and structure information for large and thick damaged areas. Various tools are available for restoring damaged old photographs. These tools require user intervention which need expertise in the software functioning and is very time consuming. So, a technique is required that can automatically reconstructs the damaged part of an image and is achieved by consulting the information from region other than damaged part, to make the final resulting image look complete and plausible. A lot of studies have been made on Image Inpainting to preserve both texture and structure information.

Inpainting algorithms can be majorly categorized in two different classes of algorithms i.e. Structure-based method and Texture based method. The structure-based method uses PDEs (partial differential equation) [1], [2] which obtains edge information for creation of linear edges from undamaged region by calculating the vector perpendicular to the gradient. Hence, this method conserves all structure information of the image. As a consequence, these techniques create some blur in the resulting image which becomes visible if reconstruction of larger regions is done. These methods perform best for images which have pure structure or thin cracks. These techniques are appropriate for reconstructing small and non-textured region. Second category is based on texture synthesis in which textures are generated for larger image regions using sample textures. Texture based algorithms fill in damaged or missed regions using rest of the available information of image, i.e. they try to match statistics of damaged regions to statistics of known regions. But these techniques are unable to build structures or edges of images.

The exemplar-based inpainting methods for texture synthesis contain the necessary procedure required to reconstruct both texture and structure. These techniques plausibly and efficiently construct new texture by replicating and sampling texture from undamaged region. These inpainting algorithms make use of priorities to conserve structure by rearranging the synthesizing procedure [3].The product of two terms, confidence term and data term, decides the priority of synthesizing order. After deciding the priority, patch-based texture synthesis techniques searches for the most similar texture and then replicate them to fill the target region. Therefore characteristic information i.e. texture and structure for large damaged regions are constructed.

This study adopts same notation which used in literature [3]. The region to be reconstructed is represented by Ω (Target region) and its contour is symbolized by $\delta\Omega$. The undamaged region from where information is used to reconstruct the target region (Source region) is represented as Φ.

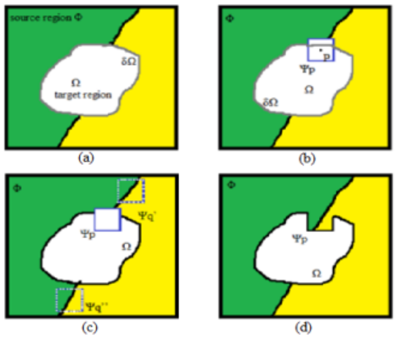


Fig.1. Structure Propagation in an image

Fig 1(a) illustrate an image, with the source region Φ, target region Ω and its contour δΩ. 1(b) shows the point p, centre of the patch Ψp Є δΩ and its surrounded area. 1(c) shows the most similar candidate patches for Ψp in the source region represented by Ψq' and Ψq'' and 1(d) shows the data propagation from the best matching patch from the candidate set, results in partial filling of Ω. Thus, the structure as well as texture is constructed and this process is continued iteratively until the entire missing region is filled.

II. Materials and Methods

The aim of this work is to propose an algorithm that can be use to reconstruct large areas of the image efficiently and accurately. The Exemplar-based inpainting model depends entirely on the priority values. The proposed inpainting algorithm provides the user with a capability of selecting the target region. This work uses a free hand selection method to draw the region to inpaint. In Exemplar based algorithms target region is replaced patch by patch. The patch generally entitled as the template window and denoted by ψ. The size of this window is defined manually for the algorithm and can be varied according to the requirement. The size is generally larger than the largest texture element in the source region. Once this parameter is assigned the remaining process is completely automatic. The proposed algorithm is an extension of Criminisi [3] algorithm and pseudo code is as follows

Input: Image

Draw target region
Initialize $C(p) = 0$ for $\forall p \in \Omega$
$C(p) = 1$ for $\forall p \in \Phi$
Do (for $\forall p \in \Omega$)
if
Ω = Null then exit.
Else
compute $P(p) = R_c(p)*D(p)$ for $\Psi_p \in \Omega$
$R_C(p) = (1-\omega).C(p) + \omega$
find exemplar patch $\Psi q \in \phi$
$d(P\Psi_p, P\Psi_q) = d_{IMED}(P\Psi_p, P\Psi_q) \times d_H(\Psi p, \Psi q)$
for $\forall p \in \Psi q$ replicate to Ψp
update $C(p)$ for $p \in \Psi p \cap \Omega$

Output: Inpainted Image

and is divided into three steps which are as follows:

2.1 Selection of patch to fill

Usually exemplar-based model uses onion-peel method as the default filling order where the target region is reconstructed from outwards to inward and a higher filling priority is given to the exemplar which holds more known information [5],[6]. Onion-peel filling generates good result, if texture pattern of single kind is build[5].But, a single image can contain more than one texture pattern, separated by linear structures so filling by onion-peel method is not suitable. So, the proposed method encourages propagation of structure along with texture by best-first filling order which depends entirely on priority values. The priority computation for the same is biased towards high-confidence pixels which are on the continuity of edges. The priorities for the patch $\psi_{p,}$ centered at a point p depends on two terms C(p) and D(p)

$$P(p) = C(p) \cdot D(p)$$

where C(p) and D(p) represents the confidence term and the data term for the patch. The confidence term relies on information in the patch which reflects the confidence in selecting that pixel. Hence, this term concentrates on filling of patches that have most of its pixels filled. The confidence term solely enforces the filling from outward to inward since the pixels on contours have more confidence value and therefore are filled prior to the pixels in the middle of the target region. The confidence value does not change once the pixel has been filled. The value of confidence term is initialized to 1 for all the pixels present in Φ(source region) and 0 value is given to the pixels of Ω (target region) and is given by

$$C(p) = \frac{\sum_{q\epsilon\Psi_p\cap\varphi} C(q)}{|\Psi(p)|}$$

here, $|\psi_p|$ represents area of the selected patch p[12]. Therefore, confidence term tells the ratio of the belief on the current patch to the belief associated with a known patch.

The data term is defined as a function of strength of the isophotes hitting the fill front. This term is more biased towards the selection of those patches that have contours in them. So, higher value of data term is given to patches having edges in them. To preserve structures, it is very important to fill these regions first. The data term is given by

$$D(p) = \frac{\left|\nabla I_p^{\perp}.n_p\right|}{\alpha}$$

Here, α represents normalization factor, n_p represents a unit vector orthogonal to the front and ∇Ip is the perpendicular isophote at point p. Calculation of n_p is done by using the gradient for source region. The data term increases with the normalization of the gradient $|\nabla Ip|$ and even when isophote becomes perpendicular to the edge. The patch will have a strong linear structure when D(p) → 1. Gradient modulus is rotationally invariant due to which accuracy calculation directly affects the image.

The priority values of patches depend on both the confidence and the data terms. Use of the confidence term and data term together assure that the patches that are filled earlier holds high confidence values and have structure too. The single priority term handles the balance for all the patches on the fill front.

The values of confidence term are consistent except on areas where strong structures information exists. It is observed that confidence terms values are decreasing too fast as its value variations are insignificant. Due to this, a regularizing function $R_C(p)$ is used in this work to stabilize the values of the C(p) to match with data term which is given by

$$R_C(p) = (1-\omega).C(p) + \omega\,, \qquad 0 \le \omega \le 1$$

where ω is a the regularizing factor which controls the curve smoothness. This work uses ω=0.7. So, the new priority function is calculated as

$$P = R_c(p)^* D(p)$$

This new priority function resists undesired noises and is robust to the abovementioned procedure. The new order of filling is more trustworthy and reliable. Now as the priorities for all the patches are computed, maximum priority patch amongst them is selected, for which the suitable information is searched from the source region.

2.2 Searching

Now as the highest priority patch Ψp is found, the next step is to search for the most similar patch from the source region Φ. The patch chosen from source region to replicate Ψp, denoted by Ψq and is known as candidate patch. Traditional inpainting techniques uses SSD(Sum of Squared Differences) as the parameter to judge the similarity of two patches[13]. This parameter focuses only on the difference of values of corresponding position of two patches ignoring the contribution of distance of current pixel to the damaged pixel. Moreover, SSD does not use the whole information enclosed in Ψq as it is constrained only on current pixel value and the region nearby this pixel [9],[2]. In [2] author pointed out that final results by this method are not visually coherent as it can select visually different patches. This study proposed an improved metric that, Image Euclidean Distance (IMED) to calculate patch distance as defined below [12],

$$d_{IMED}\ (x, y) = [(x-y)^T G(x-y)]^{1/2}$$

where, d_{IMED} (x, y) represents Image Euclidean Distance. When k-nearest patches (Ψq_i) are discovered the patch with minimum distance is selected and its information is transferred to the target region [7].

2.3 Update

After we finding the best exemplar, the patch with maximum priority selected in the first step is replaced with the best exemplar found in the previous step. Earlier, inpainting techniques use diffusion for smoothing large regions of image which can create smudge in image.

The value of each pixel of optimal patch Ψ_q is filled in the corresponding pixels of Ψ_p. After filling the target patch the confidence term of the patch is updated as follows:

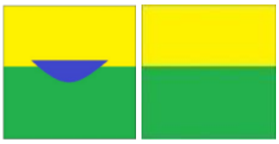
$$C(p) = C(q)$$

where C(q) and C(q) are the confidence values of patches Ψ_q and Ψ_p[14]. Without specifying image parameters this update rule measures relative confidence values of the patches of target region. The confidence values decays as filling proceeds which indicates lack of surety about pixels near the middle of the target region. This process is repeated iteratively till all the pixels on the fill-front are filled. The output of this procedure is the inpainted image.

III. Results and Discussions

A variety of pure synthetic images and colour photographs which include complex texture and structures are used to assess the efficiency of the proposed algorithm in reconstructing large objects. This method restores the texture and structure of the target region and improves inpainting efficiency. The size of patch in all the experiments is taken larger than the largest texture in the source region. The SSIM (Structural Similarity Index) and PSNR (Peak Signal-to-Noise Ratio) are the parameters used for comparison of two images. The SSIM index measures the quality of image by taking reference to the initial distortion free image. SSIM uses the available structure information of the objects in the visual scene and any change in luminance, structural information or contrast leads to image degradation.

Many real images used in this study are obtained from the literature on texture synthesis and from BSD (Berkeley Segmentation Dataset) [11]. The size of image depicts how much time is required to inpaint the target region. Block-based sampling procedure is used to achieve computational efficiency.



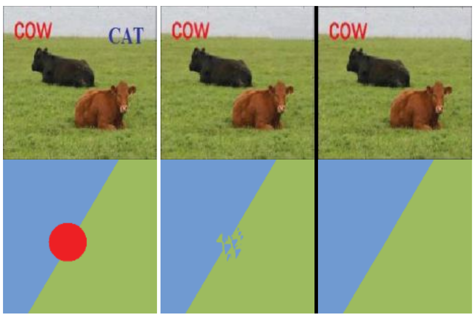
(a)

(b)

Fig. 2. Synthetic and Real Image example

The results of proposed algorithm are compared with the method of Criminisi to show improvement and the validity of this method. Figure 2(a) shows a synthetic image and its target region is in blue color. The reconstructed line smoothly continues the isophotes. Paint like program is used to draw this image manually. Figure 2(b) shows a real Image its inpainting result. Even though the size of the removed region is large, the edge in the inpainted region of both images is sharp and continues.

Figure 3 shows comparison of the proposed algorithm with the algorithm proposed by Criminisi [8]. The images in 3(a) are the original images, 3(b) shows the inpainted results images by Criminisi[8] and 3(c) shows the results by proposed algorithm. Criminisi's algorithm [8] introduces inconsistent edge structures in images and some unpleasant artifacts are introduced. Following table shows the PSNR and SSIM of various images.



(a) (b) (c)

Fig. 3. Comparison of results with Criminisi[14].

Table 1. Comparison of PSNR of inpainting results of Criminisi et al and proposed algorithm.

Image Number	PSNR of Criminisi	PSNR of Proposed method	SSIM of Proposed Method
COW	40.36	52.6359	0.9999
RED COLOR	26.48	35.2744	0.9997
GIRL	33.16	48.3513	0.9998
BIRD	33.22	47.0473	0.9998

IV. Conclusion

The experiments results show that proposed method is capable in recovering the large or small damaged region effectively maintaining the texture uniformity and the edge continuity for a good visual quality even if the missing details are complex and inhomogeneous. The improved filling order and priority term calculation of proposed algorithm shows advantages of better reconstruction of linear edges and two-dimensional texture with reduction in error propagation more robustly. The evaluations on natural and synthetic images show encouraging results and better performance than fundamental algorithm. One main problem with this method is the increment in time when target region is very large. Second it starts growing junk for some textures or stays on one place in the sample image and produce fussy copies of the original. These problems occur when the source region contains too many different types of textures which create ambiguity in finding close matches. Many exemplar-based approaches have this common constraint. Future work includes incorporation of the human-labeled structure and other feasible methods into the inpainting algorithms to recover totally removed structure. This work can also be extended to repair damaged videos and 3D data.

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