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Region Filling and Object Removal by Exempeler Based Image In painting

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Abstract Object removal from images is an image manipulation technique. Objects are removed from digital images and the hole left behind is filled by a graphical technique called inpainting in a visually plausible way. This technique can be applied not only to images consisting of simple textures but also to real life images having complex textures and color scheme. The goal in each case is to produce a modified image in which inpainted region is merged into the image so seamlessly that typical viewer is not aware that any modification has occurred. Applications in image inpainting range from removal of an object from a scene to retouching of a damaged painting or photograph.Removing elements such as stamp dates or unwanted text from a picture. Red-eye removal also is one of the applications.
Keywords: called inpainting in a visually plausible way.

I. INTRODUCTION

The modification of images in a way that is non-detectable for an observer who does not know the original image is a practice as old as artistic creation itself. Medieval artwork started to be restored as early as the Renaissance. The motive was simple, to bring medieval pictures "up to date" as to fill any gaps. This practice is called "retouching" or"inpainting". The object of Inpainting is to reconstitute the missing or damaged portions of work, in order to make it more legible and to restore its unity. The need to retouch image in an unobtrusive way extended naturally from paintings to photography and films. The purposes remain the same: to remove deterioration or to add or remove elements. In multimedia signal processing, image inpainting is the technology generally applied to the problem of automatic filling-in the missing regions of an image in a visually plausible way. Inpainting has been studied in research fields. It finds many electronic imaging applications such as photo editing , image restoration and multimedia transmission. Digital techniques are starting to be a widespread way of performing inpainting, ranging from attempts to fully automatic detection and removal of scratches in film, all the way to software tools that allow a sophisticated but mostly manual process. In the past many algorithms have been proposed. The algorithms fall into following two categories:

1) Texture synthesis algorithms
2) Image Inpainting algorithms

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The former works well for "textures" and the latter for linear "structures" which can be thought of as one dimensional patterns like lines or contours. The shortcoming of texture synthesis is that it focuses on the entire image space without giving priority to linear structures. The result will thus have distorted lines.

Inpainting technique extends linear structure to the gap by utilizing isophote information of boundary pixels. Since extension uses diffusion techniques blur is introduced in the picture.

Crimimisi's algorithm combines the advantages of above mentioned approaches in an efficient manner. The improvement over existing algorithm is that the new approach takes isophotesinto consideration, and gives higher priority to those "interesting points" on the boundary of the gap. Those interesting points are a part of linear structures, and thus should be extended into gap in order to obtain a natural look. To identify those interesting points, Criminisi gives a priority value to all pixels on the boundary of the gap. The interesting points will get higher priority and thus the linear structures would be extended first. For each pixel a patch is considered with that pixel at the centre. The patch's priority is product of two elements: a confidence term C(p)and a data term D(p). C(p) describes how many pixels are there in a patch.D(p) describes how strong isophoteis hitting the boundary.

Thus we have:

P=C(p)*D(p)

The patch with highest priority would be the target to fill. A global search is performed on the whole image to find a patch that has most similarities with target patch. The last step would be to copy pixels from source to target patch. This process continues unless all the patches are filled.

2. Key Observations in Criminisi's Algorithm The two most important observations made by Criminisi are:

1) Exemplar based Synthesis suffices
2) Filling order is critical

This section discusses the above observation in detail.

2.1 Exemplar Based Synthesis Suffices The core of this algorithm is an isophote-driven image sampling process. Exemplar based approaches perform well for 2D textures. But, in addition to that, exemplar-based texture synthesis is also sufficient for propagating extended linear image structures, called as isophotes, as well. Criminisi had important point to make , that, a separate synthesis mechanism is not required for handling isophotes.

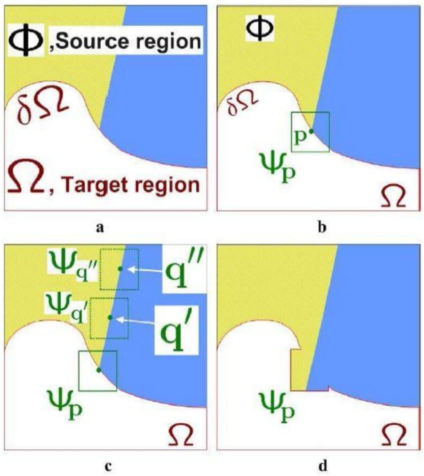


Fig .Structure propagation by Exemplar based Synthesis

Fig 1 illustrates the point. The region to be filled, target region, is indicated by Ω And its contour is indicated by δΩ The contour evolves inwards as the algorithm progresses. Hence it is referred as the “fill-front”. The source region Φ. which remains fixed throughout the algorithm provides samples used in the filling process. Single iteration of the algorithm to show how structure and texture are adequately handled by exemplar based synthesis is stated here. Suppose that the square template $\Psi_p \epsilon \Phi$ centered at point P is to be filled (fig. 1b). the best-match sample from source region comes from the patch $\Psi_q \epsilon \Phi$,which is most similar to those parts that are already filled in Ψ_p lies on the continuation of an image edge, the most likely best matcheswill lie along the same edge.

All that is required to propagate the isophote inwards is a simple transfer of the pattern from thebest-match source path. Here, isophote orientation is automatically preserved. In the figure, despite the fact that the original edge is not orthogonal to the target contour δΩ the propagated structure has maintained the same orientation as the source region. So we focus on patch basedwork as opposed to pixel-based filling.

2.2 Filling order is critical This section shows that quality of the output image synthesis is highly influenced by the order in which the filling process proceeds.

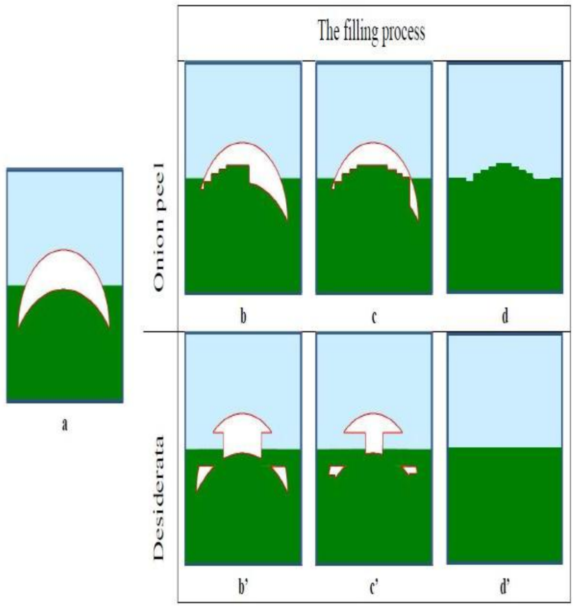


Fig . Importance of filling order when dealing with concave target regions.

A comparison between the standard concentric layer filling (onion-peel) and the desired filling behavior is illustrated in fig2. Figures 2 b,c,d show progressive filling of a concave target region via an anti-clockwise onion peel strategy. This ordering of the filled patches produces the horizontal boundary between the background image regions to be unexpectedly reconstructed as a curve. A better filling algorithm would be one that gives higher priority of synthesis to those regions of the target area which lie on the continuation of image structures, as shown in the figures 2 b’,c’,d’. Another desired property of a good filling algorithm is that of avoiding “over-shooting” artefacts that occur when image edges are allowed to grow indefinitely. The goal here is to find a good balance between the propagation of structured regions and that of textured regions without employing two ad-hoc strategies.

II. CRIMINISI’S REGION FILLING ALGORITHM

First, given an input image the user selects a target region Ω to be removed and filled. The source region, Φ may be defined as the entire image minus the target region Φ= I- Ω as a dilated band around the target region, or it may be manually specified by the user.

Next the size of window Ψ must be specified. Criminisi has stated it to be 9X9. Once these parameters are defined, the region filling algorithm proceeds automatically. In this algorithm, each pixel maintains a **color** value and a **confidence** value, which reflects confidence in the pixel value, and which is frozen once a pixel has been filled. During the course of algorithm, patches along the fill front are also given a temporary **priority** value, which determines the order in which they are filled. Then this algorithm iterates the following three steps until all pixels have been filled.

- Computing patch priorities.

- Propagating structure and texture information.
- Updating confidence values.

3.1 Computing Patch Priorities

The algorithm performs the synthesis task through a best-first filling strategy that Depends entirely on priority values that are assigned to each patch on the fill front. The priority computation is biased toward those patches which:

- Are on the computation of strong edges
- Are surrounded by high-confidence pixels

Given a patch Ψ_p centered at the point p for some p ϵ $\delta\Omega$ its priority is defined.

Priority P(p) is product of two terms:

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

C(p) is the **confidence term** and D(p) is the **data term**.

These are defined as follows:

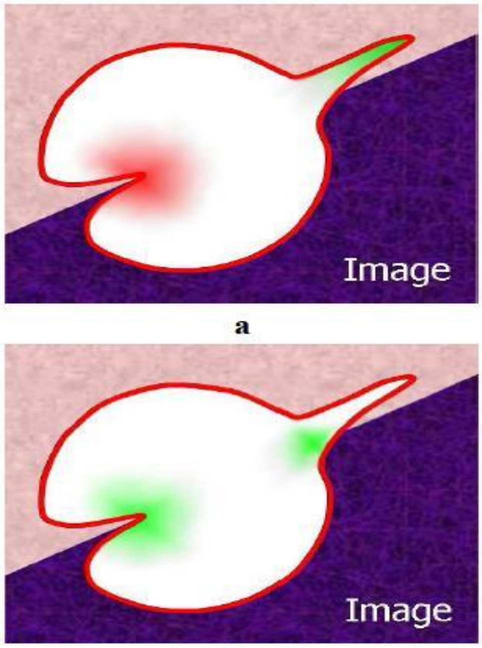
$$C(p) = (\textstyle\sum_{q\in\Psi\cap(I-\Omega} C(q))\div|\Psi p|$$

$$\mathbf{D(p)=|\Delta Ip^{\perp}.\ np|}$$

| Ψ_p |is area of Ψ_p, α is normalization factor (eg. α =255 for typical grey level image), n_p is unit vector orthogonal to front $\delta\Omega$ in point p.The priority P(p) is computed for every border patch with distinct pathes for each pixel on boundary of target region.

During initialization C(p) is set to C(p)=0 for all p ϵ Ω and C(p)=1 for all p ϵ I - Ω. The confidence term C(p) may be thought of as a measure of the amount of reliable information surrounding the pixel p. the intention is to fill first those patches which have more of their pixels already filled, with additional preference given to pixels that were filled early on.

As it is illustrated in fig 3a, this automatically incorporates preference towards certain shapes of the fill front. For example, patches that include corners and thin tendrils of the target region will tend to be filled first, as they are surrounded by more pixels from original image. These patches provide more reliable information against which to match. Conversely, patches at the tip of “peninsulas” of filled pixels jutting into the target region will tend to be set aside until more of the surrounding pixels are filled in.



a

b

Fig. Effects of C(p) and D(p)

At a coarse level, the term C(p) of eq.(1) approximately enforces the desirable concentric fill order. As filling proceeds, pixels in the outer layers of the target region will tend to be characterized by greater confidence values, and therefore be filled earlier; pixels in the centre of the target region will have lesser confidence values.

The data term D(p) is afunction of the strength of isophotes hitting the front $\delta\Omega$ at each iteration. This term boosts the priority of the patch that an isophote flows into. This factor is of fundamental importance because it encourages linear structures to be synthesized first, and, therefore propogated securely into the target region.

3.2 Propogating Structure and Sturucture Information

Once all priorities on the fill front have been computed, the patch $\Psi_{\hat{p}}$ with highest priority is found. We then fill it with data extracted from source region Φ.Image texture is propagated by direct sampling of source region. Patch which is most similar to $\Psi_{\hat{p}}$ is searched in source region . Formally

$$\Psi_{\hat{q}} = \arg\ \max_{\Psi q\ \epsilon\ \Phi}\ d(\Psi_{\hat{p}}, \Psi_{\hat{q}})$$

Where distance $d(\Psi_a, \Psi_b)$ between two generic patches Ψ_a and Ψ_b is defined as sum of squared differences(SSD) of already filled pixels in the two patches.Having found the source exemplar $\Psi_{\hat{q}}$ the value of each pixel to be fill p′ | p′ ϵ $\Psi_{\hat{p}\cap\Omega}$ is copied from its corresponding position inside $\Psi_{\hat{q}}$.This suffices to achieve the propagation of both structure and information from Source Φ to target Ω one patch at a time.

3.3 Updating Confidence Values

After the patch $\Psi_{\hat{p}}$ has been filled with new pixels values, the confidence C(p) is updated in the area delimited by $\Psi_{\hat{p}}$ as follows:

C(p) = C($\hat{p}$) for all p ϵ $\hat{p} \cap \Omega$

This simple update rule allows to measure the relative confidence of patches on the fill front, without image-specific parameters. As filling proceeds, confidence values decay, indicating less conformity of color values of pixels near the centre.

4.Psuedocode of Criminisi's Algorithm

- Extract the manually selected initial front $\delta\Omega^0$.
- Repeat until done:

1a. Identify the fill front. $\delta\Omega^t$, If $\Omega^t = \emptyset$ exit

1b. Compute priorities P(p) for all $p \in \delta\Omega^t$.

2a. Find the patch $\Psi_{\hat{p}}$ with maximum priority

Ie. $\hat{p} = \arg \max_{p \in \delta\Omega t} P(p)$

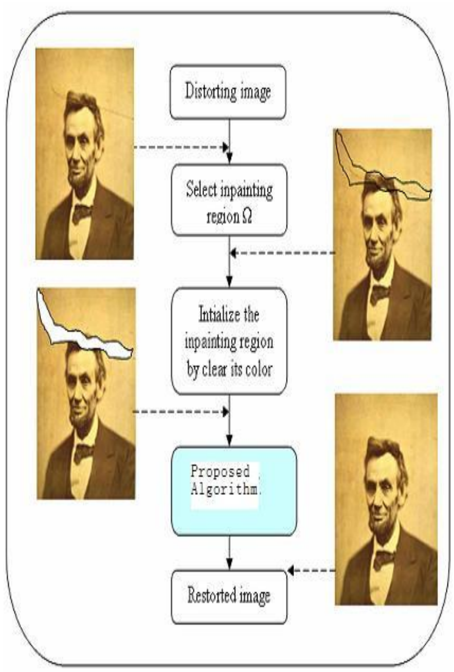
2b.Find the exemplar $\Psi_{\hat{p}} \in \Phi$ that minimizes $d(\Psi_{\hat{p}}, \Psi_{\hat{q}})$.

2c. Copy image data from $\Psi_{\hat{q}}$ to $\Psi_{\hat{p}}$ for all $p \in \Psi_{\hat{p}} \cap \Omega$.

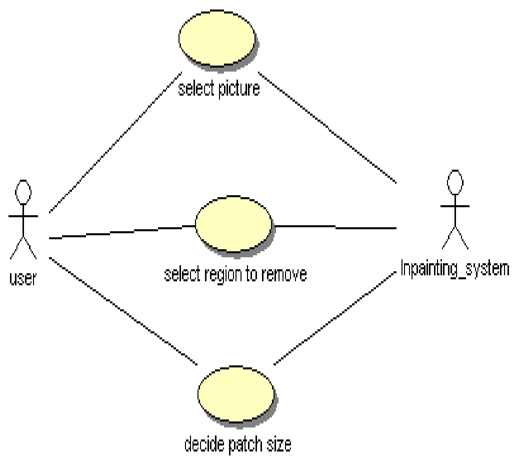
3 Update C(p) for all $p \in \Psi_{\hat{p}} \cap \Omega$.

5.Design & Design related diagrams

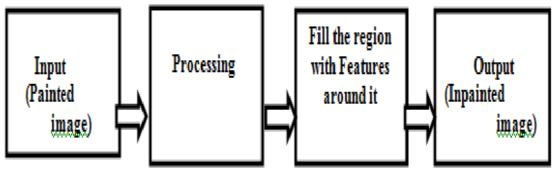
5.1 User's Point of View



5.2 Use Case Data



5.3 Data Flow Diagram



6.Properties of Criminisi's Algorithm

As illustrated in fig 3a, the effect of the confidence term is that of smoothing the contour of the target region by removing the sharp appendices and making the target contour close to circular. Also in fig 3a it can be noticed that inwards-pointing appendices are discouraged by theconfidence term. Unlike previous approaches, the presence of the data term in priority function eq(1) tends to favour inwards-growing appendices in places where structures hit the contours, thus achieving the desired structure propagation.

But, as mentioned the pixels of the target region in the proximity of those appendices are surrounding by little confidence and therefore the "push" due to image edges is mitigated by the confidence term. As presented in the results section, this achieves a graceful and automatic balance of effects and an organic synthesis of the target region via the mechanism of a single priority computation for all patches on the fill front. Eq(1) only dictates the order in which filling happens. The use of image patches for the actual filling achieves texture synthesis.

Fig. Onion peel v/s Structure guided filling

Furthermore, since the fill order of the target region is dictated solely by the priority function P(p), we avoid having to predefined an arbitrary fill order as done in existing patch-based approaches. The fill order proposed by Criminisi is function of image properties resulting in an organic synthesis process that eliminates the risk of "broken-structure" artefacts . Furthermore, since the gradient-based guidance tends to propagate strong edges, blocky and misalignment artefacts are reduced, without patch cutting or blur inducing step.

7.Implementation Details

In the implementation of this algorithm the contour $\delta\Omega$ of the target region is modeled as a dense list of image point locations. These points are interactively selected by the user via asimple drawing interface. Given a point $p \in$

$\delta\Omega$ the normal direction $\mathbf{n}_p$ is computed as follows:

1) The positions of "control" points $\delta\Omega$ are filtered via a bi-dimensional Gaussian kernel
2) $\mathbf{n}_p$ is estimated as the unit vector orthogonal to the line through preceding and successive points in the list.

Alternative implementation may make use of curve model fitting. The gradient
is computed as the maximum value of image gradient in $\Psi_p \cap I$ robust filtering techniques may also be employed here. Finally pixels are classified as belonging to the target region Ω , the source region Φ or the remainder of the image by assigning different values to their alpha component. The image alpha channel is therefore updated at each iteration of filling algorithm.

8.Results

1.Region Filling

(a)

(b)

(c)

Values of result.txt file:-

Input image File Name: nice.png

Input fill image File Name: nice_mask.png

Total no of pixels in Original Image: 38720

Total no of pixels to fill: 1124

Output image File Name: Inpainted.jpg

Total Time taken to inpainting image 36.3820

PSNR =22.9509

2.Object Removal

(a)

(B)

(c)

a)Original Image with noise added.

b)The original image has been manually selected as target region

c)Output.

9.Advantages & Disadvantages of Criminisi's Algorithm

9.1 Advantages

The advantages of Criminisi's algorithm are:

- Preservation of edge sharpness

• No dependency on image segmentation
• Balanced region filling to avoid over-shooting effects.
• Patch-based filling helps achieve speed efficiency, accuracy in synthesis of texture
and accurate propagation of linear structures.

9.2 Limitations

Limitations of Criminisi's algorithm are:
• The synthesis of regions for which similar patches do not exist does not produce
reasonable results
• Algorithm is not designed to handle curved structures
• Algorithm does not handle depth ambiguities

10.Conclusion and Future Work

III. CONCLUSION

The project involves implementing Criminis's algorithm for removing large objects from digital photographs. The result is an image in which the selected object has been placed by a visually plausible background that mimics the appearance of source region.

Criminis's algorithm employs an exemplar-based synthesis technique modulated by a unifiedscheme for determining the fill order of the target region. Pixels maintain a confidence value, which together with image isophotes, influence their filling priority.

The technique is capable of propagating both linear structure and two dimensional textures into target region with single, simple algorithm. Comparative experiments show that a simple selection of the fill order is necessary and sufficient to handle this task.

Criminisi's method performs at least well as previous techniques and in instances in which larger objects are removed, it dramatically outperforms earlier work in terms of both perceptual quality and computational efficiency.

We will implement Criminisi's algorithm and then refine it with Cheng's robust approach. The main contribution of Cheng's work is development of a generic priority function to facilitate the image reconstruction. Experimental results show that the proposed algorithm is effective in both visual quality improvement and user preference consideration. The computational complexity ofthe proposed algorithm is dominated by two tasks:

- Exemplar search
- Component weight selection.

11.2 Future Work

Future works will certainly involve investigating extensions to current algorithm to handle accurate propagation of curved structures in still photographs. Also investigation of efficient searching scheme and on the automatic discovery of component weights for different kinds of images as well as removing objects from video, which promise to impose an entirely new set of challenges

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