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Exemplar-Based Image Inpainting by Laplacian Approximation Method Using Spatiogram

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Abstract:
Inpainting is the process of reconstructing lost or deteriorated of an image. A new technique is proposed for exemplar based image inpainting. A spatiogram is an image descriptor. It combines a histogram with the mean and covariance of the position with each other. The completion of hole in the image is through Laplacian approximation method. The image is divided into small blocks based on the size of the hole. The mean shift algorithm is used to assign value to each pixel of the inpainted domain based on the pixel coloring occurring in the neighborhood pixel. The mean and the covariance of position of each color is related to ensure the continuity of the reconstruction of the boundary of the inpainting domain. Image is enhanced using histogram equalization in order to improve its quality after filling the inpainted domain. A number of examples on real images demonstrate the effectiveness of the algorithm.
Keywords—Image inpainting, spatiogram, histogram equalization, laplacian approximation method

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I. INTRODUCTION

Image inpainting, also known as image completion or disocclusion, is an active are of research in image processing. Inpainting is the process of reconstructing the lost or detorated parts of an image or video. It is usually rooted in image restoration. It aims to achieve a visually consistent boundary of the region in the image where the data is missing. It has become s standard tool for in image or video processing with many applications for scratch or text removal in photographs. Recently it also used for removing an object in the photograph and filling the hole in such a way that the removal is unknown.

Generally inpainting algorithms found in the literature can be classified as geometry or structural and exemplar based inpainting methods.

Structural inpainting uses geometric approaches for filling the missing information in the region which should be inpainted. These algorithms focus on the consistency of the geometric structure. The main problem of these structural inpainting methods is not able to restore the textures. In most cases, structural methods arelocal since they are based on PDE. They only use the information at the boundary of the inpainted domain. This methodleads to blurringartifacts in case of large missing parts. Texture is defined as some visual pattern on an infinite 2-D plane which at some scale, has a stationary distribution.The texture synthesis using non-parametric sampling technique is used for the synthesis of the textures. Efros and Leung [3] initiated this texture synthesis method. These methods rely on a sample of the desired structure to perform the synthesis. To synthesize a pixel, it first finds all neighborhoods in the sample image that are similar to pixel’s neighborhood.

Bertalmio [5]proposed a strategy to combine geometry and texture inpainting. Initially the image is decomposed into structure and texture components. Then inpaint each of them separately into structure and texture based methods. Composition of these two completed layers i.e., geometry and texture provides a completed image with no blurring artifacts. Criminisi [4] extended the texture synthesis approach by gradually propagating the information of the known region into the hole according to a priority order. The order usually influence the continuity at the inpainted domain. Sun [6] proposed a new technique by first propagating the structure and then uses the patch based texture synthesis technique for filling the remaining unknown regions.Exemplar-based texture synthesis contains the essential process required to replicate both texture and structure; the success of structure propagation, however, is highly dependent on the order in which the filling proceeds. A best-first algorithm in which the confidence in the synthesized pixel values is propagated in a manner similar to the propagation of information in inpainting. The actual color values are computed using exemplar-based synthesis. The simultaneous propagation of texture and structure information is achieved by a single, efficient algorithm. Computational efficiency is achieved by a block-based sampling process. Jia and Tang [21] proposed Tensor voting. It is a two step method first a texture based segmentation of the input image and extrapolating the region boundaries by tensor voting. Tensor voting is a very attractive method for maintaining curvature but it cannot perform well on complex structures since image segmentation of natural images is a difficult task.

Most of the exemplar-based approaches are greedy procedures i.e., each target pixel is visited only once and the results are very sensitive to the order in which they are processed.Contraryto these greedy approaches [7, 8, 12] some formulate image inpainting as a discrete global optimization problem, where the image is modeled using a Markov Random Field (MRF) with pairwise interactions. Laurent Damanet proposed a variational model of energy function, the inpainting problem is written in terms of a correspondence map. It assigns each point of the inpainting domain a corresponding point in the known part of the image. Arias proposed a non local image inpainting technique. It includes the features of geometry-based approaches by a proper choice of the similarity criterion. Here the energy function is written in terms of the known part of the image and the correspondence map. Nearest Neighbor Field (NNF) is used to reduce the computational complexity.

The optimization of energy function is a common approach for most of the exemplar-based image inpainting[8-10]. The formation of the energy function according to Liu in terms of the offset map permits to use the graph cuts algorithm to optimize the energy. The four nearest neighbors in the pairwise potentials reduces significantly the number of edges of the graph and hence the complexity is reduced. A variational formulation of Efros-Leung, [3] the inpainting problem was written in terms of correspondence map i.e., Assigning each point of the known part in the image. Arias [9] proposed a variational frame-work for non-local image inpainting that permits to include features of geometry-based approaches by a proper choice of the similarity criteria. The energy is written in terms of the unknown part of the image and correspondence map. The computational complexity is reduced by NNF (Nearest Neighbor Field).

II. EXISTING ALGORITHM

The inpainting algorithm relies on the global minimization of an energy function that enforces the structure and texture consistency. The energy function is written in terms of the offset map. It combines a data term to ensure the continuity of the reconstruction at the boundary of the inpainting domain and a term that enforces a spatially coherent reconstruction inside the hole. Graph cut algorithm is used to obtain the global minimum of this energy formation. In order to reduce the the computational complexity, graph cuts are applied using a multiscale scheme. i.e, Graph cuts are applied using a Multiscale Gaussian pyramid. Each pyramid decreases the image resolution to half in each spatial dimension. The optimization starts at the coarsest level and propagated to the finer levels for further refinement. The main reasons for using the multiscale graph cuts algorithm are: the first one is to reduce the computational cost. The second one is that the smoothness term, at each scale the 4 nearest neighbors, can capture more spatial information at the lowest resolution level. The image size at the lowest resolution is around 80 × 80, and we use 2 to 5 levels for most images. During the image downscaling from the original size to the smallest one, most of the image information, specially the structure and texture of the regions, is lost. Thus, it is easy to find wrong offset labels for pixels at lowest resolution, and is difficult to correct this at higher resolution using a small search range.

To compensate for the loss of structure and texture information at the low resolution level, a feature representation is computed at the original image resolution. In order to avoid this problem, more structure and texture information are kept at low resolution. When working in the lowest resolution grid π_{L-1} a feature vector with 7 components are used

$$u(p) = \{(u_i^{L-1}(p))_{i=1}^{3}, g_x(p), g_y(p), G_x(p), G_y(p)\} \quad (1)$$

In equation (1) u^{L-1} denotes the image at low resolution, $p \in \pi_{L-1}$,$g_x(p), g_y(p), G_x(p), G_y(p)$ are the gradient related features.

$g_x(p) = \frac{1}{2^{2L}} \sum_{q \in \gamma_p} \nabla_x I(q)$,
$g_y(p) = \frac{1}{2^{2L}} \sum_{q \in \gamma_p} \nabla_y I(q)$,
$G_x(p) = \frac{1}{2^{2L}} \sum_{q \in \gamma_p} |\nabla_x I(q)|, G_y(p) = \frac{1}{2^{2L}} \sum_{q \in \gamma_p} |\nabla_y I(q)|$.

The energy can be written as

$$\varepsilon(m) = \sum_{p \epsilon \partial\, \Omega} e_d\left(p; m(p)\right) + \lambda \sum_{(p,q)\epsilon E} e_s\,(p, q; m(p), m(q) \quad (2)$$

In equation (2) p, q are two adjacent pixels; m(p), m(q) are the corresponding offsets of p, q.Multiscale graph cut algorithms efficiently solve the energy minimization problem in which the feature vector representation are used to compare patches at low resolution, to compensate the information loss.

III.PROPOSED ALGORITHM

The proposed inpainting algorithm initially performs the spatiogram of the image. The main drawback of histograms for classification is that the representation is dependent of the color of the object, ignoring its shape and texture. Without spatial or shape information, similar objectsof different color may be indistinguishable based solely on color histogram comparisons. Hence the spatiogramis used; it is an image descriptor which provides addition information such as the mean and the covariance in addition to histogram.

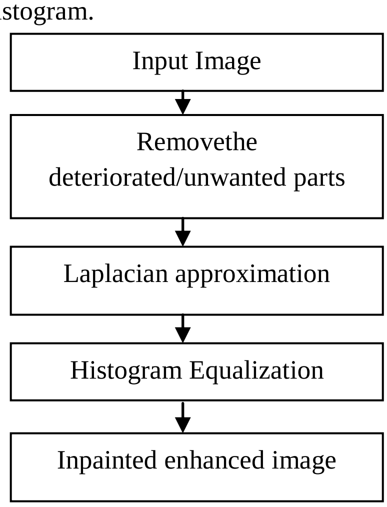


Fig 1: Proposed System design.

The steps involved are:
Step 1: Load the image.
Step 2: Segment and remove the unwanted part by means of
Connected Neighborhood Method.
Step 3: The inpainted region is filled by means Laplacian
Approximation Method.
Step 4: After filling the holein image image is enhanced by
means of histogram equalization .

The unwanted region such as scratches/text, can be removed by means of connected neighborhood method. After the image is loaded into the system, the ROIs is extracted via the Ostu segmentation method. Laplacian Approximation method is used to fill the inpainted region with the known remaining parts in the image. It is a deterministic approximation method. The cracks can be detected and it can be easily recovered by means of laplacian approximation. Images may contain textures with arbitrary spatial discontinuities, but the sampling theorem constraints the spatial frequency content that can be automatically restored. Blurring artifacts may be introduced in the boundary of the inpainted domain and hence in order to avoid these visual inconsistencies the image is enhanced by using the histogram equalization. Applying the histogram equilization method on the Red, Green, and Blue components of an RGB image may yield dramatic changes in the image's color balance. Since the relative distributions of the color channels change as a result of applying the algorithm.

(a) Connected Neighborhood Method:
The scratches/texts or the unwanted parts in the image is segmented by using connected neighborhood method. It usually segments the image into two half based on the intensity values. The region of interest is selected by Ostu segmentation. In this method the segmentation is done based on the difference in the pixel intensities.

(b) Laplacian Approximation Method:
The segmented unwanted region in the image which is obtained from the previous step is inpainted by using the Laplacian Approximation method. It is a deterministic approximation method.

Images contain both texture and structural information, the arbitrary spatial discontinuities are filled the laplacian PDF.

(c) Histogram Equalization:
The boundary of the inpainted region may contain some of the blurring artifacts and hence image enhancement is performed. Histogram equalization is an image enhancement technique in which the histogram values are equalized. The contrast adjustment is done with this and the histogram with the same level is obtained. By histogram equalization the image quality is increased by avoiding the visual discontinuity at the boundary of the inpainted domain.

IV. EXPERIMENTAL RESULTS

The proposed image inpainting algorithm is evaluated on a variety of natural images and the result obtained with our algorithm in several cases such as scratch/text removal, object removal are as follows

1) ScratchRemoval:The proposed algorithm is applied to inpaint the missing region. In photographic restoration the scratches in the old photographs can be removed by inpainting the deteriorated parts in such a manner that the visual inconsistencies are not present after inpainting the scratches.The peak signal - to- noise ratio PSNR value obtained is 41.27 dB and the processing time required to fill the scratch is 50 sec.

(a) (b)

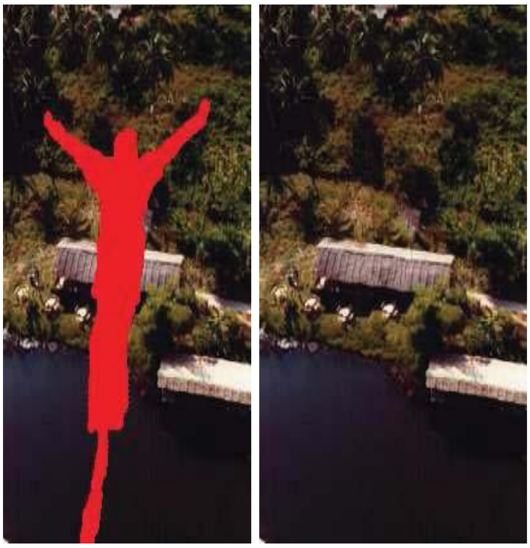
Fig 2: Result for scratch inpainting (a) Image with scratch (b) Full image which is free from scratches.

2) Text Removal: In photographic restoration text removal is an important task. The proposed algorithm is applied to remove the unwanted texts which are typed on the images. The text removal involves the selection of the ROI which is needed to be segmented. The geometric features of the image are used to fill the area. Line filling uses the structural or geometric features of an image. The peak signal - to- noise ratio PSNR value obtained is 37.18 dB and the processing time required to fill is 57 sec.

(a) (b)

Fig 3: Result of text removal (a) Image with text (b) Full image after text removal.

3) Object Removal:In photographic restoration object removal is one of the important task which is often performed. Toinpaint the images after the object removal is a challenging task because inpainting large area contains both structure and texture information. Textures are some repetitive pattern. The proposed algorithm is applied to fill those missing objects. The peak signal - to- noise ratio PSNR value obtained is 39.29dB and the processing time required to fill mask in the image is 58 sec.



(a) (b)

Fig 4: Result of object removal. (a) Image with the mask (b) Full image.

TABLE I
RESULTS OF PROPOSED INPAINTING METHOD

Images	Multiscale Graph Cuts		Proposed Method	
	PSNR	Processing time	PSNR	Processing time
1	40.47	56	41.27	50
2	35.18	74	37.18	57
3	36.32	73	39.29	58

V. CONCLUSION

The unwanted region such as scratches/texts are removed by means of connected neighborhood method and it is filled with the remaining known parts in the image by means of laplacian approximation method using spatiogram. Spatiogram is an image descriptor. Some blurring artifacts may be introduced in the boundary of the inpainted domain and hence in order to provide the visual continuity at the boundary histogram equalization is used. The inpainted domain is filled in this manner and also provides visual consistency.

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