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Research Article

Exemplar based Context Aware Image Inpainting

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Abstract

Various factors affect the image that causes image deterioration. The art of restoration of deteriorated parts of image is known as image inpainting. The proposed system focuses on context-aware patch-based image inpainting. The proposed system is Exemplar-based inpainting solution. Initially the image is divided in variable size block according to their context. The candidate patches are searched with the matched image block. The Markov random field model is used to manage the access of nearest matching patches. The image inpainting is based on surface fitting as the prior knowledge. This technique uses the angle-aware patch matching. For the matching precision between patches, the Jaccard similarity coefficient is used. This maintains the consistency of the structures and textures. The system is tested on multiple dataset images for object removal. For image quality analysis, PSNR ratio is calculated. The system results are compared with existing systems in terms of efficiency.

Keywords: *Image inpainting, Surface fitting, Angle awareness, Dynamic patch selection, Markov random field model*

Introduction

Image inpainting is also referred as image completion. This is an image processing technique in which image is visually filled at the missing region. It corrects or reconstructs the deteriorated part of an image. The image deterioration can happen due to various reasons like: environmental factors, chemical processing, improper storage and more. Image inpainting has various applications like:

1. Image restoration: It recovers the degraded or distorted part of the image and improves the appearance.
2. Image coding and transmission: Using this technique image is encoded and transmitted to the receiver end. At the receiver end image is getting reconstructed initially to display only highlighted features and as per the user requirement it gets refined. Photo editing: In photo editing image can be altered, newly created or helps to merge 2 or more images.
3. Virtual restoration: It detects and removes cracks on digitized image.

Initially M. Bertalmio et. al. [1], proposed an inpainting method to resolve the damaged and occluded parts of an image. The solution is based on formulating higher order partial differential equation, i.e. it creates Laplacian of an image. This equation propagates the information in the direction of isophotes. The proposed algorithm follows the direction of the gradient for image inpainting.

The image inpainting is categorized in two sections:

4. Diffusion based:

In diffusion-based technique, missing region is filled. The missing region is called as a hole. The hole is filled with smooth propagation from the boundary to the center of the hole. This follows the linear propagation structures. It generates good results in case of inpainting long thin region. But fails to inpaint texture-based image.

5. Patch Based:

This technique fills the image patch by patch. It searches for well-matching replacement from undamaged part of an image. Such patches can parches be also called as candidate patches. The best suited patch is copied to the required location. As compared to the diffusion-based method patch-based methods generate better results in case of texture-based image inpainting or for inpainting the larger holes.

The proposed system performs inpainting in a dynamic manner. In the process of inpainting initially the unknown region is initialize using the fitting surface method. The dynamic patch selection strategy applied to inpainting missing region. Small target patches are applied in the high-frequency region. The patches are selected from context-aware source region using angle-aware patch matching technique. To improve the patch selection process Markov random field is used. For angle-aware patch matching, the Jaccard similarity coefficient is used.

Following section II includes the related work in the same domain. Section III includes the problem formulation; section IV represents the proposed methodology followed by the result and analysis in section V and finally we have conclusion.

Literature Survey

T. F. Chan et. al. [2], proposes an inpainting method for normal non-textural images. This technique uses curvaturedriven diffusions mechanism. This technique is used in the nonlinear Partial differential equation. This paper treats on the disocclusion of image based on human vision. It treats image as 2D projection of 3D world scene. This paper deals the inpainting process as a lower level process as compared to disocclusion.

Patch based inpainting methods are categorized in following 3 categories:

1) Greedy: Using greedy technique best match is selected for filling the hole. The selected patch is called as target patch. The patch is getting selected based on its known pixels. The greedy method is an iterative method that fills the hole gradually.

2) Multiple candidates: In this type of methods, multiple matched patches are selected from other undamaged part of an image. The missing region is filled with weighted average or sparse combination of multiple combinations of patches.

3) Global: This method treats the inpainting as a global optimization problem. Here also multiple candidates are chosen. Such candidates are selected for different positions in an image. These candidates are known as labels. Labels for each position are selected in such way that it minimizes the global optimization function.

Zhang, et. al. [3], proposes an angle aware patch inpainting. It initially initializes the target patch that is to be removed using surface fitting and MIS method. This system uses a dynamic patch selection process. In the high-frequency region, small target patches are applied, whereas in the low frequency region, large patches are applied. The system uses the angleaware patch matching. For this Jaccard similarity coefficient is used. The patch is searched from all the regions of images. This is a time-consuming process.

Q. Cheng et. al. [4], proposes a multichannel nonlocal total variation model for inpainting. This system deals reconstruction problem of remotely sensed images. In this technique surrounded part and silent region is inpainted first and then the remaining one.

V.B.S. Prasath et. al. [5], proposes a diffusion-based method. The system works on works on ill-posed image processing problems. The inpainting process works on limited data set. The system works on lower structures of texture and geometric constructions. The system takes only small-scale natural images. The inpainting area should be small. For large missing region or complex textures, the resultant image contains an inconsistency of structure and texture, unpleasant artifacts. The generated image is over-smoothed.

H. L Zhao et. al. [6], proposes a GPU based inpainting method. A coherent direction-aware patch alignment algorithm is proposed. GPU speeds up the patch searching process and enhances the similarity among matched patches. The execution time reduces as compared to the other methods. S. Darabi, et. al. [7], proposes a fast patch based image inpainting method called as patch match. The main disadvantage of patch based method is its efficiency. In patch based method system searches for different candidate patches. This candidate generation process is time consuming and exhaustive. This is a structural image editing method using randomized algorithm. It quickly finds the best match patch by approximate nearest neighbor match. This paper proposes an interactive image editing tool.

T. Ruzic, et. al. [8], proposes a context-aware patch-based image inpainting method. In this technique textural descriptors are used to find best matching candidate patches. This technique divides the image in unequal size of blocks based on its context. This is a global image inpainting method. It uses Markov random field to encode a priori knowledge of other neighboring candidate patches. Due to Markov random field evaluations the number of candidate patches is getting filtered and hence candidate size gets reduced. For contextual descriptors texton histograms is proposed. This histogram finds the texture within a local region.

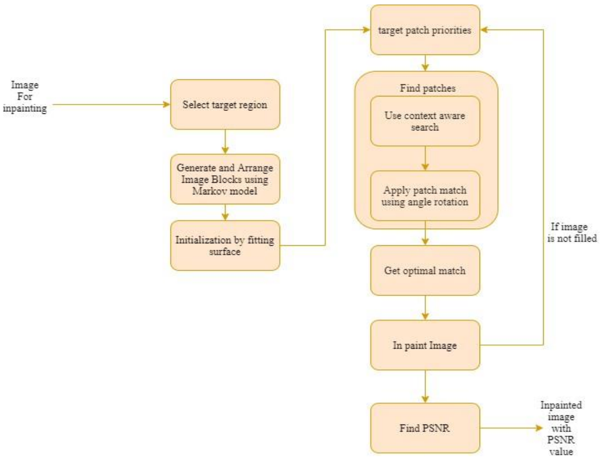
Problem Formulation

Based on the literature review patch based inpainting method generates better image inpainting results as compared to the diffusion-based method. Angle-ware rotation patch matching strategy which considers the different angles of the same source patch in order to find multiple candidate patches for every target patch and improves the matching accuracy. The Context aware patch based method using MRF helps to reduce the number of possible candidate patches, and helps to improve efficiency if inpainting method. From the matched contextual block, the matched patch identified. MRF method improves the system efficiency. There is need of such system that helps to find angle aware target patches from context aware source region to inpaint texture-based images efficiently.

Proposed Methodology

A. System Architecture

Following figure 1 shows the architecture of a system. The image to be inpainted is input to the system. The block to be inpainted is selected by the user. The system generates inpainted image with its PSNR value as an output.



B. Preliminaries:

1) Texton Histogram:
This is used for image texture representation. The procedure for texton calculation is as follows:

a) Extract 5x5 sized image patches
b) From center of each image patch
c) Subtract the mean rgb value of the pixels in that patch
d) Cluster the image patches using K-means
e) Centroids of the K clusters are the textons
f) Compute a K dimensional histogram of texton

2) Markov random field model:
For matching best patch from image and the image patches are searched from other part of the image. To improve the efficiency of searching patches the image patches are arranged using a Markov random field model. The network of similar patches is generated using Markov random field. This is an undirected graph. For a Markov random field generation following steps are carried out:
a) Divide the image in adaptive size blocks based on intensity and color.
b) Find texton of the image.
c) Generate a Graph (V, E) where V are patches and E represents set of edges with similarity in texton values.

3) Surface fitting technique
This method is used to initialize the pixel values for the missing region of an image. The process of surface fitting technique is as follows:
a) Find the grey value of each pixel
b) Project the image pixels from 2D space to 3D space by adding height as grey value
c) Apply moving least square method

C. System Working:

The image is given as input to the system. A region to be removed is selected by the user. Based on the user input, the initial image is divided into adaptive size blocks. And contextual descriptor using Texton histogram is assigned to the patches. The Markov random field model is used to manage generated blocks in a chain. For patch matching several suitable candidate blocks are selected for patch search. The method focuses on replacing the missing region using textural and structural similarity. Initially the unknown pixels in the missing region are initialized by surface fitting technique. In second phase filling order is defined using a priority function. Filling of the image is started from the boundary point to the inner section. Based on the gradient value target patch is selected. Then for a filling inner section of target region various patches are selected using angle rotation strategies from the source region. The selected patch is placed in the image and then again priority is checked for next filling order this is an iterative process. After completing the image inpainting, PSNR value of an image is calculated.

D. Algorithm:

Algorithm: Exemplar-based Context Aware Image Inpainting
Input: I: Image to be inpainted
T_i: target area in image *Output: IP:* Inpainted Image
res: PSNR value

Processing:

1. T: Select target region Mask Image region
2. Find Image Blocks using Gradient difference
3. Arrange Image blocks using Markov Model
4. Initialize target patch using moving least squares (MLS) method
5. Calculate of the target patch filling priorities from boundary
6. Find Patches using Markov chain
7. Apply patch match using angle rotation
8. Get optimal match
9. Inpaint Image I
10. Is target image Not filled
11. go to step 5
12. Calculate PSNR
13. Display result

E. Mathematical Model:
The record data normalization system S can be defined as:
S = {I, O, F}
Where
I = {I1, I2}, Set of Inputs
I1 = Image
I2 = Target region
O = {O1, O2}, Set of Outputs
O1= Inpainted Image
O2 = PSNR of Image
F= {F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F11, F12, F13, F14, F15, F16}, Set of Functions
F1 = Upload Image
F2 = Select target region Mask Image region
F3 = Generate Image Blocks
F4 = Arrange Image blocks using Markov Model
F5 = Initialization By fitting Surface

F6 = Moving least squares (MLS) method
F7 = Calculation of the target patch priorities
F8 = Find Target Patch Priorities F9 = Find Patches
F10 = Using context Aware Search
F11 = Apply patch match using angle rotation
F12 = Get optimal match
F13 = Inpaint Image
F14 = Save Image
F15 = Calculate PSNR F16 = Display result

Result and Discussions

The system is implemented in java using jdk 1.8. For image processing opencv3.1 library is used. The system is implemented on windows 10 machine with 4gb RAM and core I3 processor.

A. Datasets:

The image dataset is downloaded from Berkeley [9] and downloaded ICME 2019 Grand Challenge [10]. The Berkeley dataset contains 1,000 Corel dataset images from 30 human subjects. The ICME 2019 Grand Challenge dataset contains large-scale, high-quality, carefully crafted 1500 high-definition natural, complete images.

B. Performance Measures:

1. Time: The time required for image inpainting with existing system and proposed system is calculated.
2. PSNR: Peak signal to noise ratio between original image I and inpainted image I' is calculated as:

PSNR = 10 $log10$ (MSE ______ $MAX(I,2I')$)

Where,

MAX = largest gray value of image color. It is set to 255 MSE is a mean squared error. It is calculated as:

$$MSE = M\frac{1}{} \sum * n \quad n_{i=1} \sum_{j=1}^{m} |I'(i,j) - I(i,j)|_{||^2}$$

I = Original image I' = Inpainted Image n = Image height m = Image width

C. Implementation Status:

The system implementation is done partially. The user interface is created using which user can upload the image that need to be inpainted. A panel is provided to the user to select the area to be inpainted. After area selection, the image is divided into variable sized block as per the context information. The Markov chain is created to save the block information.

Fig. 2. System Results

Above figure 2 contains three images. The first image is input to the system. The second image represents the area that needs to be inpainted and the third image represents the context aware variable sized blocks.

Conclusions

The proposed system focuses on context-aware patchbased image inpainting. The proposed system is Exemplarbased inpainting solution. Initially the image is divided in the variable size block according to their context. The candidate patches are searched with the matched image block. The Markov random field model is used to manage the access of nearest matching patches. The image inpainting is based on surface fitting as the prior knowledge and an angle-aware patch matching. Jaccard similarity coefficient is used to advance the matching precision between patches and to maintain the consistency of the structures and textures. In future system will be implemented for the scratch and text removal of an image.

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