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Removing an Object Using MRF Patch-Based Image Inpainting

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Abstract: ***A methodology for context-aware patch-based image inpainting is presented in this paper. Here textural descriptors are used, which controls and accelerates the search for nearest patches. The input image is inpainted by using a non- parametric patch sampling. Here, we have used the Markov random fields (MRF) for getting nearest patches on input image for better results. The computational complexity is reduced by the inpainting of the input image and it also allow to work with the dominant orientations of image structures. Image super-resolution is applied so as to recover the details of missing areas from the low-resolution inpainted image. Natural images and texture synthesis are used to demonstrate the effectiveness of the proposed method.***

Keywords: Inpainting, patch-based image inpainting, texture features, context-aware,Markov-random-field modelling,object removal

1. Introduction

The process of image inpainting can be defined as the task which fills the missing or the distorted region of the given image. It can also be called as an art of refilling the image with new values according to the needs. Image inpainting has large scope of applications, which includes image restoration for e.g., removing scratch or text; it is also used in photo editors, for e.g. object removal, crack removal of digitized paintings, etc.

The basic idea behind the inpainting techniques is that the inpainting method always uses the information of the known part in order to fill the required inpainted part. In image inpainting the image can be divided in to two parts that is one is source region and target region. Source region is the region which includes the region comes under known part of image. Target region is the region comes under the required inpainted part of image. In inpainting algorithms, the target region is calculated by analyzing the source region. It is a general concept behind the inpainting techniques. As the technology advances, there are various types of data sets that have been used in these technologies, images area also one of the important types of data used widely in the recent technologies. The concept of inpainting allow images to be more adaptable to the required environment. The number of images has also increased the need for tools which automatically search collection of images. Although tools based on keywords exist, they have two major drawbacks. Firstly, each image in the collection has to be described by keywords which are time consuming. Secondly, the expressive power of keywords is limited and cannot be exhaustive. Hence, image content based tools are required, for example in stock photo agencies.

In this paper, an approach of inpainting is proposed which is a patch based image inpainting. Patch based image inpainting is one of the type of inpainting in which the image inpainting is done by replacing the missing area by similar patches of that area. In addition to patch based image inpainting, a MRF is used for better results.

This paper consists of the different sections as section II describes literature survey of the topic. Section III states about implementation details, introductory definitions and documentation, Section IV represent dataset and expected result Section V talks about conclusions and presents future work.

2. Literature Survey

O. Le Meur, M. Ebdelli, C. Guillemot [2] introduced a hierarchical exemplar based inpainting concept. In this algorithm, first the image is inpainted using exemplar based inpainting. After the inpainting, the details of missing areas are recovered by the proposed hierarchical based super resolution algorithm. This approach can be used in both low resolution as well as high resolution images. For the low resolution images, the results are more distinct and better in visual quality.

T. Ruzic, A. Pizurica, and W. Philips [3] address the concept of the neighborhood message passing technique for the image inpainting. This paper proposes a concept for the loopy belief propagation networks. It makes it better by using message passing techniques. This technique is for the networks with large number of nodes. Iterated conditional expectation algorithm is used in this algorithm.

J. Lee, D. K. Lee, R. H. Park [4] presents an algorithm for image inpainting; this algorithm is exemplar based algorithm. It uses region segmentation concept for the exemplar based algorithm. In this algorithm, the source region is iteratively searched to get the similar patch so as to fill the target region. It uses segmentation method to utilize information of the source region. Performance is improved by using the segmentation map.

T. Ruzic, A. Pizurica, and W. Philips [5] paper introduces a concept of patch based image inpainting using MRF modeling. In this paper, the top down splitting approach has been proposed to divide the image in to adaptive size according to their context. In this approach, contextual descriptors are used to accelerate the search of well matching candidate patches. It also proposes a concept of MRF to be applied to global image inpainting, which gives prior knowledge about the well matching candidate patches. An inference method is applied to solve the optimization problem.

P. Arbelaez, M. Maire, C. Fowlkes, and J. Malik [6] proposed an algorithm which deals with the two main problems of the computer vision; that are, contour detection and image segmentation. The contour detection is removed by the detector which combines the information of local image and global image. A method is also proposed to convert the contour signal into the region hierarchy which also preserves the contour quality.

O. L. Meur, C. Guillemot [7] presents a technique for the image inpainting on local geometry. It is an exemplar based inpainting technique. This technique is derived by combining the advantages of the two inpainting techniques; that are potential differential equation based technique and exemplar based technique. This technique uses two factors that are structure tensors and template matching. Structure tensors are used to define priority of filling order at the basis of order of hierarchy. Templates matching are calculated on the basis of K-nearest map algorithm.

Z. Xu, J. Sun [8] presents examplar based image inpainting technique. In this, the inpainting technique deals with the Sparsity of images. Two factors are used to in patch based image inpainting so as to deal with the Sparsity; that are patch priority and patch representation. The factor patch priority is used to measure the patch confidence. This technique provides better results as compared to the traditional inpainting approaches.

A. Bugeau, M. Bertalmio, V. Caselles, and G. Sapiro [9] proposed a combine mechanism of the image inpainting which consists of the three basic concepts; that are texture synthesis, potential differential equation and neighboring pixel method. Combination of these three techniques provides better performance of the image inpainting instead of using each separately.

A. Torralba, K. P. Murphy, W. T. Freeman [10] presents a framework to encode the relationship of the context and the object properties of the image. In this, the contextual information is represented without using the object. It also describes a method to integrate the object representation with the object detector.

3. Implementation Details

A. System Overview

This system proposes a mechanism of the MRF modeling for context aware patch based image inpainting. The context aware patch based image inpainting is the method used to inpaint the image by using the contextual descriptors so as to guide the process. These descriptors also improve speed of the process. This process consists of two approaches:

- Contextual descriptor approach.
- MRF based inpainting approach.

A Contextual descriptor approach is an approach in which the search of the candidate patches is accelerated. With this method, the patches of the area of interest are searched based on the contextual feature. The main idea is to first divide the image in either fixed or adaptive sized blocks. Assign the contextual descriptors to the image blocks. Well matching patch can be found by comparing contextual descriptors.

An image can be divided into the regions on the basis of the context by two methods; simple fixed sized non overlapping squares and adaptive sized blocks. For the division into adaptive sized blocks a top down procedure is followed. It consists of following parts:

- Find source and target region
- Division of image into patch.
- Assigning contextual representation

In context aware MRF based inpainting, an optimization approach is introduced. This optimization approach is based on the inference method so as to make the inpainting suitable with large number of labels. It allows the processing of larger images faster and also it consumes less memory. As there is large number of labels assigned to the patches of the image, it is very lengthy process to check for each label to check for well matching patch. Hence MRF optimization is used for the label pruning, which reduces the time requirement of the inpainting process.

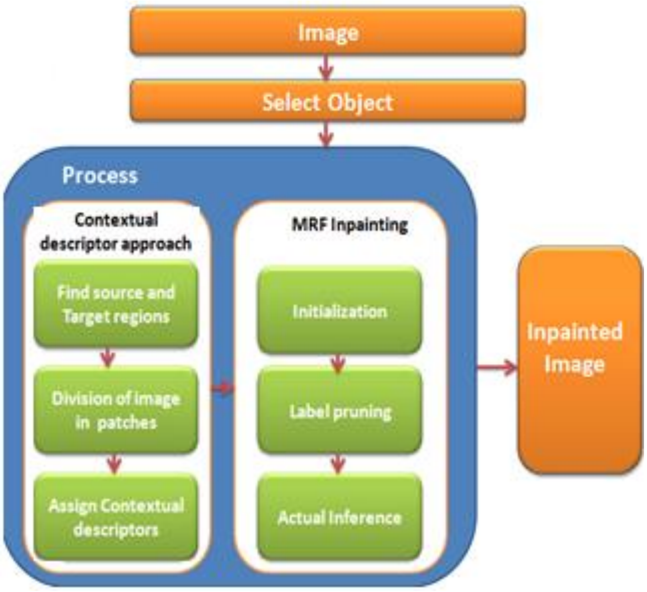

Figure 1: MRF model for context aware patch-based image inpainting Architecture

This context aware MRF based inpainting section consists of 3 sub sections, which are: Initialization, Label pruning and Mean calculations, and Actual Inference. After these two procedures i.e. context aware patch based approach and MRF-modeling, new required inpainted image is obtained.

B. Algorithms

Here, we used following algorithms to achieve the result.

1) Context-Aware Patch Selection Algorithm

Context-Aware Patch Selection Algorithm is a method which is one of the most popular unsupervised learning algorithms due to its simplicity. The Context-Aware Patch Selection Algorithm for image segmentation can be carried out as follows.

a) Analyze the inpainting patch context.
b) Match the context to minimize the patch and maximize the result.
c) Adapt the communication mediation appropriately.

2) Markov Random Field Algorithm

MRF algorithm is carried out as follows.

a) Consider an image with target part.
b) Inpainting consists of creating a sequence of images.
c) Then for every pixel (horizontal), we get mean of its surrounding blocks pixel to fill that patch. This process will repeat until all pixels get filled with some RGB value in horizontal.
d) Same method is repeated for vertical pixels also to fill the pixels with mean RGB value.

C. Mathematical Model:

1) For step 1, context aware patch selection,
Let I is the input image defined on lattice S.
Each pixel position p on S is represented by p € S.
Let Ω € S denote target region and
ϖ € S denotes source region.
Therefore,

$$\Omega \cup \varpi = S.$$

2) Dividing image I into M * N blocks.
Let Bl is block at l'th position.
Select source region ϖl for Bl.
Let c^l is contextual descriptor for block at l position.
$H^{(l,m)}$ Represents measure of contextual dissimilarity.
Therefore, the measure of dissimilarity is given by:

$$H^{(l,m)} = d\left(c^{(l)}, c^{(m)}\right) \tag{1}$$

Where, $d(c^{(l)}, c^{(m)})$ represents distance measured between blocks at l and m positions.

3) Let ∑(l) denotes set of positions of the block that are contextually similar to Bl.

$$\sum(l) = \{m \mid H^{(l,m)} \leq \tau \wedge m \in \lambda\} \tag{2}$$

Where τ is some block similarity threshold.

4) Constrained source region is then a union of known parts of block indexed in a ∑ (l):

$$\varpi^{(l)} = U_{m\in\sum(l)}(B_m \cap \varpi) \tag{3}$$

5) For step 2, Division into blocks of adaptive size, Splitting is takes place in both horizontal and vertical direction alternatively. For this, each block is assigned with directional flag,

$$\delta(l) \in \{h, v\}$$

Where h is horizontal,
v is vertical direction.

6) Let block B is splits in to two sub blocks, Bl1d and Bl2d then the inhomogeneity of block Bl is measured along direction d.

It is given by using contextual dissimilarity equation:

$$H_d^{(l)} = H^{(l_{1d}, l_{2d})}, \text{ d= h, v.}$$

7) For the next step, an optimal combination of source region candidates for target region results in the energy optimization given by:

$$E(x) = \sum_{i\in v} V_i(x_i) + \sum_{<i,j>\in\varepsilon} Vij(x_i, x_j)$$

4. Results and Discussions

a) Dataset used

To implement the MRF modeling for context aware patch-based image inpainting system described above, we used the Stanford dataset for image inpainting.

b) Results

1) Selecting the image to be inpainted.

Image that is to be inpainted is to be selected by user from this window shown in fig 4.1.

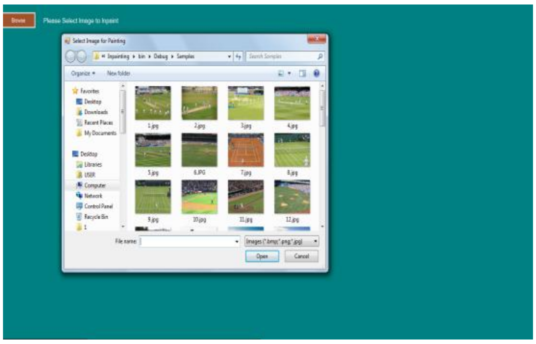

Figure 4.1: Select image to inpaint

Figure 4.2: Selected image to inpaint

2) Selecting the object to remove

User needs to select the object from the image so as to remove it from the image.

Figure 4.3: Select object to remove from image

In fig 4.3, the object to be removed from image is selected by the red color.

3) Applying the system to inpaint the image

By applying the proposed system, the selected object is removed and the image is inpainted as shown in figure 4.4.

Figure 4.4: output of the proposed system

5. Conclusion and Future Scope

A MRF modeling for the context aware patch based image inpainting is introduced here. This inpainting method uses a context aware approach. By using this approach, the numbers of labels per MRF node are reduced. Contextual descriptors are used to represent the context either by fixed or adaptive size block. In this paper, the image is divided into the regions which use the concept of top down splitting so as to divide the image into adaptive size blocks. A simple method is proposed for optimization by reducing the labels of each node. To reduce the labels it uses the node agreement and contextual similarity of region and label.

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