Research article Available online www.ijsrr.org ISSN: 2279–0543

International Journal of Scientific Research and Reviews

A Novel Exemplar Based Image Inpainting Method

Joshi Pranjali and Shrivastava Neeraj*

Computer Science and Engineering, Institute of Engineering and Science, IPS Academy
Indore, India
E-mail: Pranjali1992cs@gamil.com

ABSTRACT:

Image inpainting is the research area in the field of image processing whose goal is to remove some objects or restore the damaged regions in a way that observers cannot notice the flaw. There are many applications of image inpainting such as photo editing, video editing, image compression and image transmission..in this paper we have proposed a novel exemplar based image inpainting technique. This method uses a novel mean square error formula. This formula helps in selection of the best patch to be inpainted. This thing ultimately helps in producing a good quality inpainted picture. The good thing with this method is that it selects the best patch in less time.

KEYWORDS: Image in painting, Region filling, wavelet transform ,Robust method ,Exemplar based in painting.

***Corresponding author name**

Neeraj Shrivastava

Professor, Computer Science and Engineering

Institute of Engineering and Science, IPS Academy

Indore, India

E-mail: neeraj0209@gmail.com

INTRODUCTION:

Generally image inpainting techniques can be categorized into two approaches; Diffusion-based and Exemplar-based approaches. Diffusion-based approach is the fundamental approach in which information diffuses from known region into missing region. The problem is usually modeled by Partial Differential Equation (PDE), so sometimes it is called a PDE-based approach. Diffusion-based approach works well for non-texture image, in which the missing region must be small and thinner than the surrounding object. In the case that the missing region is large or containing texture, this approach gives a blurry result.

Exemplar-based approach is originated from the Exemplar- based texture synthesis in [1.] In that work, the texture is synthesized by copying the best match patch from the known region. However, as there are both structures and textures in natural images, directly applying Exemplar-based texture synthesis to image inpainting problem may not provide satisfactory result. Bertalmio[2] proposed to decompose the image into structural and textural images, then apply Diffusion-based inpainting to the structural image and texture synthesis to the textural image separately. The result of combining restored structural and textural image is better than restoration by only Diffusion-based inpainting or texture synthesis alone. For Exemplar-based texture synthesis to determine the fill-in order Criminisi et al. [3]introduced patch priority, which is defined by isophote direction and the known region in the target patch, Comparing with Diffusion-based inpainting, Exemplar-based approach gives a better result even in the large missing region case.

Image In painting Algorithm

Mainly there are three classes of algorithms employed for inpainting. The first class of algorithms is for restoring films or videos, but it is not very useful for image inpainting as there is limited information for inpainting images as opposed to film inpainting where the information may be extracted from various frames. Second class of algorithms deals with the reconstruction of textures from the image [4]. Algorithms utilize samples from the source region to rebuild the image. By using this approach, the most of the texture of the image can be rebuilt. Third class of algorithms tries to rebuild the structural features such as edges and object contours etc. Authors of paper [1] presented a pioneering work in this respect. This was able to recover most of the structural features from the image but failed while recovering huge regions. Author in [6] used the concept of mask to achieve inpainting. Mask that they choose for inpainting is decided interactively and requires user intervention. Method prepare the mask such that the centre element in the mask is zero. It means that no information about a pixel is extracted using its own value. Algorithm uses the values of its neighbouring pixels to determine its value. It also works only for small regions and cannot inpaint large regions in the image.

One more algorithm for recovering small regions and noise in an image is proposed in paper [5]. This can inpaint images with very high noise ratio. Method uses Cellular Neural Networks for the same. The noise inside the cell with different sizes are inpainted with different levels of surrounding information. This method achieved a high accuracy in the field of de-noising using inpainting techniques. Method provides results that show that an almost blurred image can be recovered with visually good effect. It is not suitable for the larger regions.

The [7] propose an algorithm using Cahn-Hilliard fourth order reaction equation to achieve inpainting in gray-scale images. Author in [2] enhanced the working of the [7] by introducing variable flow of images.

Method in [4] proposed an inpainting algorithm to fill in holes in overlapping texture and/or cartoon image synthesis. Author constructed a decomposition based method and filling-in stage as two blocks. On the other hand, their approach [1,4] considers these as one unified task.

Outline of Proposed Work:

The outline of the proposed work is as follows:

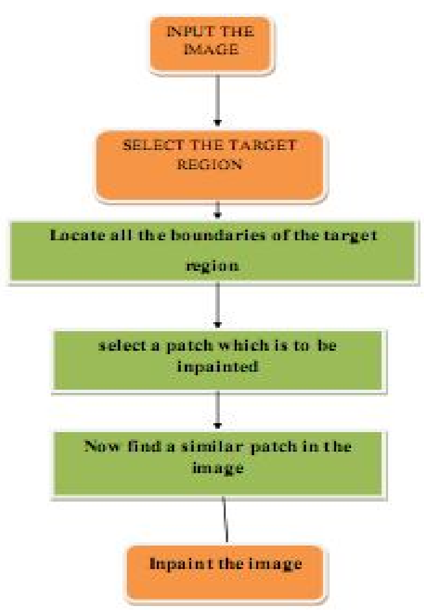

Fig 1: Outline of the proposed work

The NMSE (Normalised Mean Square Error) is an estimator of the overall deviations between predicted and measured values. It is defined as:

$$NMSE = \frac{1}{N}\sum_{i}\frac{(P_i - M_i)^2}{\overline{P}\,\overline{M}}$$

Contrary to the bias, in the NMSE the deviations (absolute values) are summed instead of the differences. For this reason, the NMSE generally shows the most striking differences among models. If a model has a very low NMSE, then it is well performing both in space and time. On the other hand, high NMSE values do not necessarily mean that a model is completely wrong. That case could be due to time and/or space shifting. Moreover, it must be pointed out that differences on peaks have a higher weight on NMSE than differences on other values.

RESULTS OF THE PROPOSED WORK:

- Use of NMSE will select the best patch which will do the task with less time as compared to the existing base paper method.
- Also the quality of the picture produced has improved as new criteria allows to select the best possible patch.
- Proposed method is capable of handling the curved structures
- It can work on all images. Some existing methods for inpainting works on some specific images.
- We have implemented the proposed methodology & the existing robust method, the time taken by our method is almost half the existing method.

Fig 2:Image before inpainting

Fig 3:Image after inpainting

Algorithm Name	Time Consumed
Previous Approach:	**143910 ms**
proposed method:	**60898 ms**

Table 1: Time Required by the Existing and the proposed method:

CONCLUSION:

In this paper, we have proposed a novel exemplar based method for the image inpainting. It will remove the existing object. It is fast in comparison to the existing method. Also it is capable of producing high quality output images. The novel normalized mean square formula has allowed to fetch the best patch for inpainting. So the picture quality has improved. It is also consuming less time.

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