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Review on Inpainting techniques for Image restoration and modification

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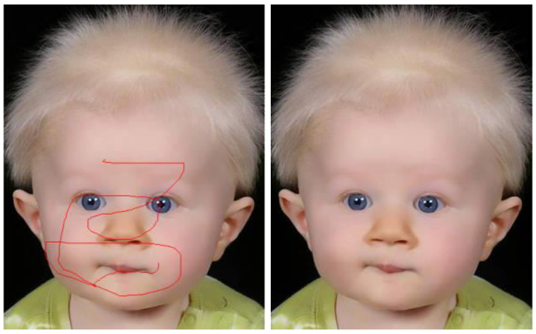
Abstract -An art of image Inpainting is in demand since decades wherein digital images are modified in such a way that the modifications/alterations are undetectable to an observer who is unknown of the original image. The technique is applicablefor restoration of damaged photographs & films, removal of superimposed text, removal/replacement of unwanted objects. In past the problem of inpainting was addressed by two classes of algorithms (i) "diffusion based inpainting" and (ii) "texture synthesis". Further extensive research has undergone in this field which resulted in variety of inpainting techniques. In this paper we will have a review on two categories namely sequential and CNN(Convolutional Neural Network) based inpainting techniques.Sequential-based approaches are the proposed methods without deep learning using neural networks. Where the CNN-based approaches are the algorithms that use neural networks with automatic deep learning

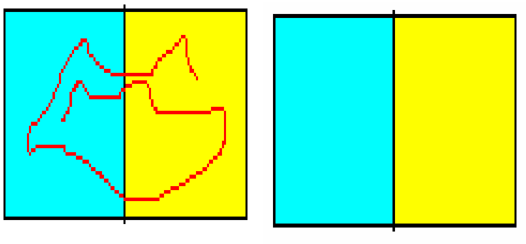
***Key Words*:**Exemplar, Inpainting, Texture synthesis, Object removal, CNN

1. INTRODUCTION

In today's digital world people are clicking images every now and then, they may want to preserve these images either in hard or soft form and also they may have old pictures with them. The issue related to hardcopy is that the pictures may get deteriorated by the time; as far as soft copy is concerned one may wish to remove or replace unwanted objects from the image. Therefore so many times it is needed to have a system to recover the damaged photographs, to perform artwork design, to modify the image etc. That means removal of portions of an image is an important tool in photo editing and film post-production. The unknown regions can be filled in by various interactive procedures such as clone brush strokes, and compositing processes. Such interactive tools require meticulous work driven by a professional skilled talented artist to complete the image seamlessly. This process is time consuming and leads manual errors in reconstruction. the problem of image completion was addressed by two sets of algorithms which are (i) inpainting [Bertalmio et al. 2000 [5]]- which works well in reconstructing linear structures such as small scratches, and (ii) texture synthesis [Efros and Leung 1999 in [7]]; Wei and Levoy 2000 [6]; Efros and Freeman 2001 [4]] which works well for repetitive two dimensional textures. The objective of image inpainting technique is to reconstruct both structure and texture of damaged image in a visually plausible manner.



(a)



(b)

(c)

(d)

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Fig. 1 Examples of image inpainting (a) Removal of scratches from real image (b)removal of scratches from synthetic image (c) Removal of single object(signboard)(d)Removal of multiple objects

As shown in Fig. 1 inpainting can be applied to real as well as synthetic images to remove unwanted object or scratches on the photographs. In this paper we will review different image inpainting techniques. This paper gives review on some of the sequential based and CNN based techniques of image inpainting techniques.

2.1 SEQUENTIAL BASED INPAINTING TECHNIQUES:

The sequential-abased approaches are the proposed method without deep learning using neural networks. They are catagorised as structure based, texture based and exemplar based methods of inpainting as explained below.

2.1.1 STRUCTURE BASED IMAGE INPAINTING:

The first inventor of inpainting, in the context of image processing was Bertalmioet. al. [5] in year 2000, where a Partial Differential Equation i.e. PDE- based inpainting is proposed in the context of real painting recovery. PDE-based image inpainting has been identified an effective field of investigation . In case of Total variation model for image inpainting, the interpolation of this model can construct straight isophotes, not only significantly evenly continued from the boundary but also do not consistently apply the Connectivity rule. The algorithm[5] propagates the necessary information by arithmetically determining the Partial Differential Equation.

2.1.2 TEXTURE BASED IMAGE INPAINTING

Structure based inpainting are suitable mainly for missing regions of small areas which propagate neighboring information into the missing region. Hence to inpaint large missing areas, texture information is used. Sung Ha Kang et al [8] presented an approach to inpaint large missing regions in an image with the help of global information from multiple images. This inpainting approach has following three phases: 1) Extraction of landmarks and matching. 2) Interpolating directional information. 3) Copy information from one image to another. If the inpainting shows some irregularities in the intensity levels in the modified image then local inpainting techniques can also be used along with the interpolation to improve the final result. Most techniques which uses global information for inpainting are related to textural inpainting. Anat Levin et al. proposed one such technique which is based on histograms of local features and uses exponential family distribution over images [9]. Probability of image is given by small number of sufficient features which are taken from arbitrary location from image.

2.1.3EXEMPLAR BASED INPAINTING ALGORITHM:

Both texture synthesis and diffusion have their own advantages and drawbacks for image inpainting. Diffusion allows the continuity of contours but gives blurred results whereas Texture synthesis permits to conserve the textures but usually fails at preserving the edges and big structures.Bertalmio M, L. Vese and G. Sapiro in [3] presented a work that decomposes the original image into two components, one of which is processed by inpainting and the other by texture synthesis. The output image is sum of two processed components. This approach is limited to the removal of small image gaps because the diffusion process continues to blur the filled regions and also the approach avoids the automatic switching between “pure texture” and “pure structure mode”. Criminisiet. Al. [1] proposed an algorithm that combines the advantages of these two approaches into a single efficient algorithm in exemplar based inpainting. An algorithm uses isophote driven image sampling process. It takes known image patches i.e. exemplars and propagates them into the missing regions. To handle the missing region with composite textures and structures, patch priority is defined to encourage the filling order of patches on the structure.

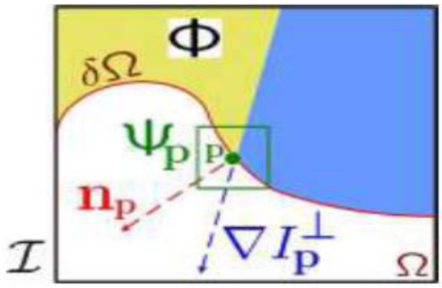

Fig.2. Notation diagram

First, given an input image I, the user selects a target region Ω to be removed and filled. The source region Φ is defined as the entire image minus target region (I- Ω) see fig 2. which remains fixed throughout the algorithm it works as a dilated band around the target region or it may be manually specified by the user. The source region provides samples used in the filling process. The contour of the target region is denoted by δΩ which is also referred as “fill front”. The size of template window Ψ must be specified. Once these parameters are determined the algorithm proceeds automatically. The heart of this algorithm is priority/ patch orderingmechanism that allows exemplar based approach to handle the structural features of an input image. Priority is composed of two terms- Confidence term denoted by C(P) and the data term D(P)both are defined over pixels.

- $C(p) = (Sum_{\{q \backslash in\ \Psi p \backslash intersect\ (I\text{-}\Omega)\}} C(q)) / (area\ of\ patch\ )$
- $D(p) = abs(Isophote(p). Normal(p)) /alpha$

Confidence term is a measure of reliable information surrounding the pixel P.Confidence tends to decay as the centre of the fill region is approached. Confidence is used to capture the texture property but it ignores structural information in the image because of which if priority only consisted the confidence term, the patches would be selected in an “onion peel” manner which may lead to visible artifacts such as unrealistically broken structures.The data term D(P) is the function of how strong an isophote hits the boundary/contour δΩ at each iteration. An isophote is basically the gradient at a pixel rotated by 90 degrees, it captures the "strength of flow" of an edge. It encourages the linear structures to be synthesized first and therefore propagated securely into the target region. Broken lines tend to connect, thus realizing the "connectivity principle" of vision technology. But If only the data term is used in the priority, however, edges end up propagating where they shouldn't.

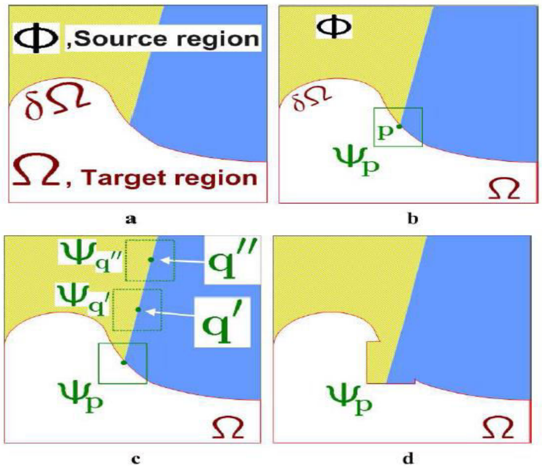

Fig 3. Structure propagation by exemplar-based texture synthesis

Now let us focus on a single iteration of this algorithm to show how structure and texture are adequately handled by exemplar based synthesis. Suppose that the square template Ψ_P ЄΩ centred at the point P [Fig.3(b)] is to be filled. The best-match sample from the source region comes from the patch Ψq Є Ω. , which is most similar to those parts that are already filled in Ψp. In the example in Fig. 3(b), we see that if Ψp lies on the continuation of an image edge, the most likely best matches will lie along the same (or a similarly colored) edge [e.g., Ψq' and Ψq'' in Fig. 3(c)]. All that is required to propagate the isophote inwards is a simple transfer of the pattern from the best-match source patch [Fig. 3(d)].

From above discussion it is seen that PDE-based techniques inseminate information from the edges of a missing region towards the center which is applicable for reconstructing a damaged image where small regions are lacking. Texture synthesis based methods are not applicable to structural information whereas PDE-based techniques lead to frequently occurring blurring artifacts. As a result of which both of them can't handle general inpainting. A patch-based approach, besides that, is much more relevant for image inpainting as a result of which it can generate high-quality visual effects while also cultivate flexibility of local structures.

2.2 CONVOLUTIONAL NEURAL NETWORK-BASEDMETHODS:

CNN-based approaches are the algorithms that use neural networks with automatic deep learning.

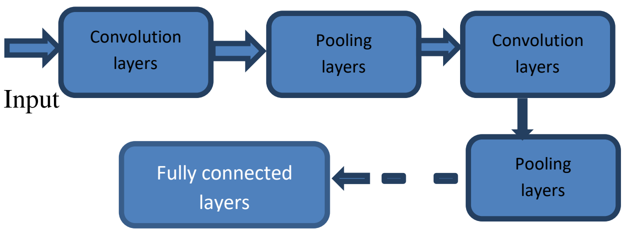

Fig.4 Block diagram of CNN

As shown above in fig.4 there are three types of layers in a convolutional neural network: convolutional layer, pooling layer, and fully connected layer. Each of these layers has different parameters that can be optimized and perform a different task on the input data. The patch of image is taken and applied to convolution layers which are nothing but set of filters that process or activate image data which is then applied to pooling layers which are nothing but nonlinear down sampling layers which perform a specific function such as max pooling, which takes the maximum value in a certain filter region, or average pooling, which takes the average value in a filter region. These are typically used to reduce the dimensionality of the network. The similar process of convolution and pooling is repeatedly performed until specific information about the image is obtained; finally the processed data is passed through fully connected layers for classifying the image data.

Recently, the strong potential of deep convolutional networks (CNNs) is being exhibited in allcomputervisiontasks,especiallyinimageinpainting. CNNsareusedspecificallyinorder to improve the expected results in this field using large-scale training data. The sequentialbased methods succeed in some parts of image inpainting like filling texture details with promising results, yet the problem of capturing the global structure is still a challenging task [12]. Several methods have been proposed for image inpainting using convolutional neural networks (CNNs) or encoder-decoder network based on CNN. Shift-Net based on U-Net architecture is one of these methods that recover the missing block with good accuracy in terms of structure and fine-detailed texture [12]. In the same context, Weerasekera et al. [13] use depth map of the image as input of the CNN architecture, whereas Zhao et al. [14] use the proposed architecture for inpainting X-ray medical images. VORNet [15] is another CNN-based approach for video inpainting for object removal. Most image inpainting methods know the reference of damaged pixels of blocks. Cai et al. [16] proposed a blind image inpainting method named (BICNN). Based on convolutional neural networks (CNNs)usingencoder-decodernetworkstructure, manyworkshavebeenproposedforimage inpainting. Zhu et al. [17] proposed a patch-based inpainting method for forensics images. Using the same technique of encoder-decoder network, Sidorov and Hardeberg [18] proposed an architecture for denoising, inpainting, and super-resolution for noised, inpainted and low-resolution images, respectively. Zeng et al. [19] built a pyramidal-context architecture called PEN-NET for high-quality image inpainting. Liu et al. [20] proposed a layer to the encoder-decoder network called coherent semantic attention (SCA) layer for image inpainting method. Further, Pathak et al.[21] proposed encoder-decoder model for image inpainting. In order to fill the gap between lines drawing in an image, Sasaki et al. [22] used an encoder-decoder-based model. This work can be helpful for scanned data that can miss some parts. For the UAV data that can be affected in terms of resolution or containing some blindspots, Hsu et al. [23] proposed a solution using VGG architecture. Also, for removing some text from the images Nakamura et al. [24] proposed a text erasing method using CNN. In order to enhance the images of the damaged artwork, Xiang et al.[25]alsoproposedaCNN-based method.

3. CONCLUSION

Imageinpaintingisanimportanttaskforcomputervision applications,duetolargemodified data using image editing tools. From these applications, we can find wireless image coding and transmission, image quality enhancement, image restoration and others. In this paper, a brief image inpainting review is presented. Different categories of approaches have been presented including sequential-based (approaches without learning), CNN-based approaches. Toconclude,thereisnomethodthatcaninpaintalltypesofdistortion inimages,butusing learningtechniquesprovidessomepromisingresultsforeachcategoryoftheanalysedcases.

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