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A Survey on Different Techniques used for Image Inpainting

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Abstract - *In today's world of technology Digital image inpainting has become a popular area of research within the field of image processing. Digital image inpainting has important applications in the area of computer vision with the development of various image processing tools and techniques. The main objective of inpainting is to restore the damaged or missing regions in an image. The goal of this survey is to provide an insight into the work that has been done in the field of Image inpainting. There are different methods available for image inpainting process and all those methods have their own advantages and disadvantages. The proposed work presents a comprehensive survey of various image inpainting techniques available and relative study of those techniques and various inpainting dataset and evaluation metrices are also discussed. Depending on different approaches used for image filling, digital inpainting techniques can be grouped into mainly two categories like Classical or Traditional inpainting approaches and Deep Learning-based approaches.*

Key Words**: Image Inpainting, Deep Learning, Diffusion, Generative Adversarial Network, Semantic, Perceptual.**

1. INTRODUCTION

Nowadays, image is one of the most common forms of information that is used in every domain of life which is captured by using digital cameras or other capturing devices. In our daily life, images can be very helpful for purposes like authentication, encryption, sharing, processing etc. Moreover, we all use images and videos to store the memories of our important moments, but due to extra part or distortion in images, sometimes useful images get discarded or deleted. Different type of distortion including blocks, text, scratches, lines, or masks can be removed by the use of image inpainting techniques. Many powerful photo-editing tools are available for removing lost information from images. But the process of filing the missing information or reconstruct damage area in an image is still difficult task.

Image In-painting has received a remarkable attention in the past few years and has become a very well-known field of research in image processing. The concept of image inpainting commonly known as disocclusion or image completion actually derived from ancient art of restoration method. The main aim behind image inpainting is to restore missing regions where the restoration is done in such a way that it is non-detectable by human eyes. There are various application for digital image inpainting in our actual life such as error recovery of videos and images, restoration of damaged old printing and old photographs, for removing special effects like dust spots, scratches from images, multimedia editing, transmission loss, replacing large and irregular holes in an image or video for privacy protection, red eye correction, object elimination in the digital photographs, image coding, in film postproduction, removing superimposed text like subtitles, dates, time etc. Image inpainting process can be used to remove any type of distortion in the input image. The below fig.1 represents different types of distortion. Removing unwanted text in the image can be done with the inpainting process for removing unwanted text, stamps, copyright logos, etc., in digital images. Fig.1 first column shows an example of images with superimposed text. The second column indicates noisy images which can be removed by the inpainting techniques. Removal of unwanted objects in the image is one of the main applications of inpainting which is possible to eliminate unnecessary artefacts from the image using in-painting techniques. Unnecessary mask can also be removed from the image using inpainting.

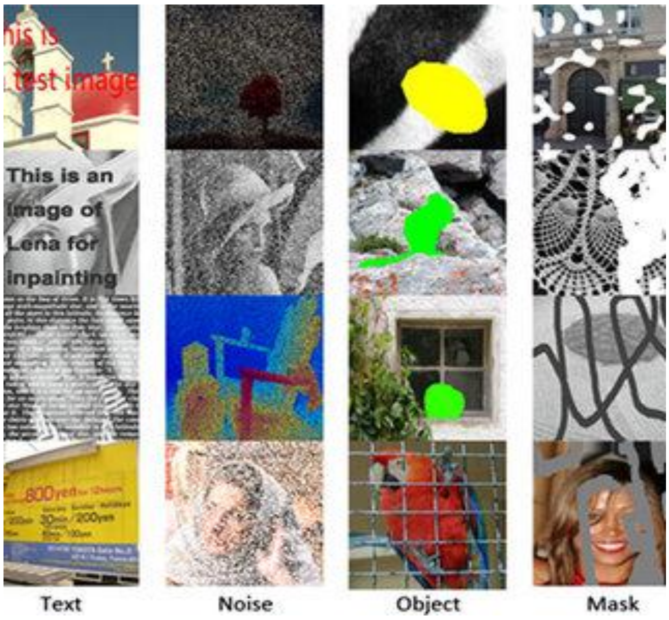

Fig-1: Types of distortion

This paper gives a brief description of different techniques for digital image inpainting. Section two presents a literature survey on different inpainting techniques, section 3 presents various inpainting dataset and section 4 presents different evaluation metrices.

2. LITERATURE SURVEY

In most of the inpainting techniques, the known information in the corrupted image is used to fill the gaps in the image. Based on the nature of applying the information, image inpainting methods can be mainly categorized into two types such as Non learning based approaches or traditional approach and Learning based approaches or neural network-based approach.

2.1 Classical Approaches

The classical image inpainting approaches also known as traditional approach or Non learning based approaches which does the inpainting process on the basis of certain algorithms and it can be categorized into two types: Diffusion based methods and Patch based methods.

2.1.1 Diffusion based method

Diffusion based Inpainting was the first category of digital image Inpainting technique. Diffusion based inpainting approach is also known as Partial Differential Equation (PDE). This is Non learning based traditional approach which involves a diffusion process. In the diffusion-based image inpainting process the missing region of the corrupted image is filled by the process of diffusion. The missing region is filled by diffusing the image information from the known region of the corrupted image to the target region at the pixel point in such a way that the changes made is undetectable by the observer. This method performs inpainting based on the information such as isophote direction (in an image, a contour of equal luminance) and global image statistics. Diffusion based method utilizes the concept such as PDE (Partial Differential Equation) and variational methods. The PDE based method is an iterative algorithm in which the geometric and photometric information are propagated from the known region of the image to the interior portion of the unknown regions. The main advantage of diffusion-based method is that it maintains local intensity smoothness and it produce better results for non-textured regions. The main drawback is that blurring is introduced when handling larger missing regions. Thus, Diffusion based image inpainting approaches are suitable for relatively smaller and non-textured regions.

In 2000, Bertalmio *et.al* [1] proposed an iterative algorithm known as Partial Differential Equation based algorithm. The proposed algorithm is based on both geometric and photometric information. When the user selects the region to be inpainted, the algorithm automatically fills the regions in the image to be inpainted. The algorithm mainly uses the concepts of isophotes. The missing regions are filled by smoothly propagating both the local geometrical and photometric information from the borders of the image into the center of the missing part along the isophote directions. This method is found suitable for filling the small missing regions, but due to anisotropic diffusion it produces blurring.

In 2001, Ballester *et.al* [2] for filling-in regions of missing data in digital images introduced a variational approach. The proposed approach is based on joint interpolation of the image gray-levels. The basic idea behind the approach is to smoothly propagate both the vector field obtained from the image gradient and the corresponding gray values inside the holes in the image. A set of second order PDEs were developed to propagate the gradient orientation and gray levels. The method is best suited for filling in thin missing regions and the drawback is that blurring is introduced and also it tends to over smoooth the image.

In 2001, T. Chan *et.al* [3] introduces a Curvature Driven Diffusion (CCD) model for image inpainting process. The method was introduced in order to handle the curved structures. This method follows a third-order PDE model to improve the second-order total variation inpainting model introduced earlier. This method is well suitable for repairing edges for gray scale images.

In 2002, Shen *et.al* [4] formulated image inpainting as a variational problem and proposed a variational image inpainting model based on Total Variation (TV). The model uses isophote driven approach in which more promising information are used to complete the occluded images. TV based model were well suitable full inpainting smaller regions and for filling geometrical shapes. This model has the lowest complexity and ease of computing when compared to other inpainting techniques. The main drawback is that it is unable to restore large textures and is also unable to restore partially degraded images.

In 2004, Telea *et.al* [5] proposed a fast-marching method for image inpainting in order to speed up the existing inpainting process. Fast Marching Methods treats the missing region in an image as level sets and uses the fast-marching algorithm to propagate the missing information in an image. In this fast-marching algorithm, the image smoothness is estimated along the image gradient. The weighted average of known image neighborhood of pixels is used to estimate the smoothness of image. The algorithm is relatively simpler to implement and produces identical results.

2.1.2 Patch based method

Patch-based methods are also known as non-parametric methods which fills in the missing region patch-by- patch by searching for well-matching replacement patches (i.e., candidate patches) in the undamaged part of the image and copying them to corresponding target location. Patch based method is based on texture synthesis based Inpainting. As they are composed of structures in form of edges, this algorithm has difficulty in handling natural images. The method introduces the notion of patching and these algorithms are used to replace the damaged pixel using the similar neighborhood to complete the missing region. Most of the inpainting technique utilized these methods by copying the patches from known image data and duplicating it to fill the missing region because a similar patch doesn't exist for all generic images. The patch-based models consider the patch as the fundamental element in the image instead of the pixels, in order to perform searching and matching of missing portions. This method is best suited for filling-in large regions.

In 2004, Criminisi *et.al* [6] proposed an algorithm for Region filling and removing large objects from digital images by exemplar-based image inpainting. In the proposed algorithm, confidence in the synthesized pixel values is propagated in a manner similar to the propagation of information in inpainting. The algorithm makes use of both structure and texture information in the images. This approach suffers from the common problem of greedy algorithm. Better results are obtained only if the missing region consist of simple structures and textures. And it is impossible to synthesize desire image if there are not enough samples in the image.

In 2005, Jian *et.al* [7] proposed a novel approach to image completion, which is known as structure propagation. In this proposed method by extending a few curves or line segments from the known to the unknown regions, the user can manually specify the missing region structure information. The image patches are synthesized using patches selected around the curves in the known region, along the user-specified curves in the unknown region. By enforcing structure and consistency constraints, structure propagation is formulated as a global optimization problem. Structure propagation is solved using Dynamic Programming, if only a single curve is specified. And Belief Propagation algorithm to find the optimal patches, if multiple intersecting curves are specified. After structure propagation is completed, then the remaining unknown regions is filled in using patch-based texture synthesis.

In 2010, Zongben *et.al* [8] proposed two concepts of sparsity at the patch level, for modelling the patch representation and patch priority and these are two important steps for patch propagation in the exemplar-based inpainting approach. In the first step by the sparseness of its nonzero similarities to the neighboring patches, a patch structure sparsity is designed to measure the confidence of a patch located at the image structure. Higher priority will be assigned for the patch with larger structure sparsity for further inpainting. In the second step, the sparse linear combination of candidate patches can be used to represent the patch to be filled, under the local patch consistency constraint in a framework of sparse representation. The patch sparse representation forces the inpainted regions to be sharp and consistent with the surrounding textures and enables better discrimination of structure and texture.

In 2017, Qiang *et.al* [9] proposed a Two Stage Low Rank Approximation method. Traditional methods of painting based on low-rank priors generally need to resolve a convex optimization problem to recover the corrupted pixels by an iterative algorithm of singular value shrinkage. The author therefore proposes a simple method for painting images using low rank approximation, which avoids iterative shrinkage that takes time. In particular, if similar patches of a corrupted image are identified and reshaped as vectors, it is possible to build a patch matrix by collecting these simulations. This patch matrix is low-rank due to its columns being highly linearly correlated. The proposed method uses a low rank approximation with truncated singular values instead of using an iterative singular value shrinkage scheme to derive a closed-form estimate for each patch matrix. The rank of each patch matrix is empirically determined by a heuristic procedure, depending on the observation that there is a separate gap in the single patch matrix spectrum. Thus, a two-stage low-rank approximation (TSLRA) scheme is designed to recover image structures and refine texture details of corrupted images, inspired by component decomposition painting algorithms.

In 2018, Ding *et.al* [10] Proposed Image Inpainting Using Nonlocal Texture Matching and Nonlinear Filtering. In order to achieve natural-looking inpainted pictures, a new image inpainting algorithm that can replicate the underlying textural information using a non-local texture measure is used and also smooth pixel intensity seamlessly. A Gaussian-weighted nonlocal texture similarity measure is suggested to obtain several candidates for matching texture. Patches for each target patch. An alpha-trimmed mean filter is applied to the candidate patches to compute the intensity of the pixel to inpaint the target patch pixel by pixel.

2.1.3 Deep Learning based method

While several techniques for image completion have been suggested such as patch-based and diffusion-based. It remains as a difficult problem, as it often needs high-level scene identification. Not only do textured patterns need to be completed, it is also necessary to consider the anatomy of the scene and the things to be completed. In all computer vision tasks, especially in image painting, the strong potential of deep convolutional networks (CNNs) has recently been shown. Using large-scale training data, CNNs are used explicitly in order to boost expected outcomes in this area. Deep convolutional neural networks have the potential to learn strong depictions of photographs which have been extended to various degrees of success in inpainting. Recently, semantic image painting was conceived as a problem of image generation and solved within the sense of Generative Networks adversarial (GAN).

In 2016, Deepak *et.al* [11] presents an unsupervised visual feature learning algorithm based on context-based pixel prediction. The suggested approach uses Context Encoders which are convolutional neural network (CNN) that are trained to produce the contents of an arbitrary image region based on its environment. The proposed context encoder learns a representation that captures not only appearance but the meaning of the visual structures. A latent feature representation of that image with missing regions is generated by taking input image by the encoder. This feature representation is taken by the decoder and the missing image content is produced.

In 2017, Satoshi *et.al* [12] present a novel image completion method that results in images which are compatible both globally and locally. Images of arbitrary resolutions can be completed by filling in missing regions of any shape with the help of a fully-convolutional neural network. The approach uses global and local context discriminators to train this image completion network, that are trained to distinguish real images from completed ones. In order to determine whether it is coherent as a whole the global discriminator looks at the entire image, while the local discriminator looks only at a small area centered on the completed region to ensure the local consistency of the patches generated. The image completion network is then equipped to fool the two discriminatory background networks, requiring it to create images that in terms of overall accuracy as well as information, that are indistinguishable from real ones.

In 2018, Zhaoyi et.al [13] in order to fill in missing regions of any form with sharp structures and fine-detailed textures, add a new shift-connection layer to the U-Net architecture, namely Shift-Net is proposed. The encoder function of the known area is moved to act as an approximation of the missing parts for this reason. To minimize the distance between the decoder feature after the fully linked layer and the ground-truth encoder feature of the missing sections, a guidance loss is placed on the decoder feature. With such a restriction, it is possible to use the decoder function in the missing region to direct the change of the encoder function in the known region. The Shift-Net training is further developed by an end-to-end learning algorithm.

In 2018, Guilin *et.al* [14] proposed Image Inpainting using Partial Convolutions. Current methods of inpainting images based on deep learning use a regular convolutional network over the corrupted image, using convolutional filter responses based on both real pixels and the substitute values in the masked holes. This also results in artefacts such as discrepancy in colour and blurriness. Usually, postprocessing is used to minimise such artefacts, but it is costly and can fail. Therefore the handling of irregular mask is suggested by Partial Convolutional Layer and this layer consists of a masked and renormalized convolution operation followed by a mask-update level.

In 2019, Jinsheng *et.al* [15] proposed a novel and successful approach that combines the advantage of the conventional method and deep learning method with a series of links that use the coarse image created by the deep generative model to search for the most appropriate similar patch. The addition of Laplace loss to standard loss accelerates model convergence when training the model. Additionally, when searching for similar patches, region weight (RW) is established, which makes edge link more normal. The issue of blurred outcomes in the deep generative model and dissatisfactory semantic knowledge in conventional methods is solved by this approach.

3. IMAGE INPAINTING DATASET

There are many publicly available datasets for Image inpainting purpose in order to evaluate different inpainting methods and to compare their performance. The effectiveness of each proposed method is determined by the categories of images. The categories of images include natural images, face images, artificial images and several other categories.

Paris StreetView [16] is a dataset collected from Google StreetView which represent a large-scale dataset that contains street images for many cities around the world. The Paris StreetView dataset is composed of 15000 images. The images in the dataset have resolution of 936×537 pixels.

Places datasets [17] is built for visual understanding and human visual cognition purposes. The dataset includes many scene categories such as streets, synagogue, bedrooms, canyon and others. The dataset is composed of 10 million images where each scene category contains more than 400 images. This dataset allows the deep learning models to be trained with a large-scale data.

Depth image dataset [18] is introduced for evaluating the depth image inpainting methods. The dataset is composed of two types grayscale depth images and RGB-D images. 14 different scene categories are included such as Motorcycle, Piano, Adirondack, Jade plant, Playable and others.

Foreground-aware dataset [19] includes masks that can be added to any images for damaging it. Foreground-aware datasets contains 100,000 masks with irregular holes for training the model, and 10,000 masks for testing the model. Each mask is a gray image of size 256 x 256 with 255 indicating the hole pixels and 0 indicating the valid pixels. The masks can be added to any image for which can be used for creating a large dataset of damaged images.

ImageNet [20] is a large-scale dataset containing over 14 million images with thousand different categories of images. The current version of the ImageNet dataset contains more than 14,197,122 images where the 1,034,908 annotated with bounding box.

CelebFaces Dataset Attributes (CelebA) [21] is a large-scale face attribute dataset with over 2 lakh celebrity images, with 40 attribute annotations each. Wide pose variations and background clutter are covered in the photos in this dataset.

SceneNet dataset [22] is a dataset that provides semantic segmentation, object detection and 3D reconstruction for scene comprehension tasks. This dataset contains 5 million images including the RGB image and the corresponding RGB-Depth images.

4. EVALUATION METRICES

The method of evaluation of the obtained results for image inpainting algorithms differs regarding the technique used for inpainting purpose. For the classical inpainting approaches, metrics used for evaluation are unlike CNN-based methods. The assessment of image quality can be evaluated by using qualitative and quantitative measures. The qualitative measures include a human judgment for the analysis of image quality, whereas quantitative measures include different statistical methods.

4.1 Qualitative measure

Qualitative comparison is carried out in order to take both visual and semantic coherence into account. Perceptual evaluation is used for comparing the visual results with the help of a human judgement. Therefore, qualitative comparison holds a decent and stable approach for comparing the visual results of different inpainting methods.

4.2 Quantitative Measure

In addition to the visual comparison, inpainting results on different methods are compared quantitatively. The quantitative comparison involves various statistical measures such as Mean Square Error (MSE), Peak to Signal Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM).

Mean Square Error (MSE) is computed by mean of the squared intensity differences of the pixels of the original image with respect to the test image.

$$MSE\,(s,t) = \frac{1}{AB}\sum_{p=1}^{A}\sum_{q=1}^{B}(s_{pq} - t_{pq})^2 \qquad (1)$$

Where, $A \times B$ the size of the reference and test images is, s is the original image and t is the test image.

Peak to Signal Noise Ratio (PSNR) is the widely used quantitative measure for inpainting. It is used to evaluate the variation among the individual pixel values. If the original image and inpainted image are alike, then the PSNR value is high, whereas if the original image and inpainted image is different, then the PSNR value is low. It is also suggested to have a positive correlation with the quality scores. And it is noted that if MSE reaches zero, the PSNR value approaches infinity, indicating that the higher PSNR value indicates better image quality.

$$PSNR = 10\left(\frac{\log_{10}(255)^2}{MSE\,(s,t)}\right) \qquad (2)$$

Structural Similarity Index Measure (SSIM) evaluates the similarity of the two images as a whole from three aspects of brightness, contrast, and structure. The value of SSIM range is [0; 1]. The larger the SSIM value, then higher the image similarity.

$$SSIM = d(s,t) \times e(s,t) \times f(s,t) \qquad (3)$$

Where,

$$d(s,t) = (2\mu_s\mu_t + C_1)/(\mu_s{}^2 + \mu_t{}^2 + C_1) \qquad (4)$$

$$e(s,t) = 2\sigma_s\sigma_t + C_2/\sigma_s{}^2 + \sigma_t{}^2 + C_2 \qquad (5)$$

$$f(s,t) = (\mu_{st}{}^2 + C_3)/(\sigma_s\sigma_t + C_3) \qquad (6)$$

where C1, C2, C3 are positive constants and Equation (4) reflects luminance comparison which computes the adjacency of mean luminance (μs and μt) of two images, Equation (5) reflects contrast comparison which estimates the adjacency of contrast of two respective images which is calculated by standard deviation σ_s , σ_t, Equation (6) reflects structure comparison which evaluates the correlation coefficient between the two images s and t and $\sigma_s\sigma_t$ and t is the covariance between s and t.

5. CONCLUSION

The main aim of this paper is to provide an insight into different methods for image inpainting. Image inpainting refers to the use of different techniques to replace the missing or corrupted parts of the image data. Different methods for image inpainting like classical image inpainting and Deep learning-based image inpainting techniques are studied. For each of the method, the inpainting procedure followed by its advantage and disadvantage are also discussed. Additionally, in this paper various dataset as well as different evaluation metrices including quantitative as well as qualitative measures for image inpainting are also described.

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