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A Review on Image Inpainting Techniques

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Abstract
We can see people clicking picture and putting efforts to store them. But with time pictures get damaged. To recover pictures from those damages like scratches, graphics image inpainting technique can be used. Image inpainting technique either completes or removes the missing region in images. It's one among the highly challenging topic in image processing area. Image inpainting techniques are divided into traditional techniques and deep learning techniques. It starts with introduction, types of image inpainting, literature review, discussion and the conclusion.

Keywords: image inpainting, deep learning

1. Introduction

We need methods to recover damaged photographs; where in damages have occurred due to various regions like scratches, overlaid text or graphics. Image inpainting is a technique which removes the damaged region or unwanted object from the photograph and gives good looking photograph (1). Digital imaging suites such as Photoshop and Corel Draw are the automatic methods of recovering the damaged photograph (2). In computer graphics image inpainting plays a significant role. Because in various applications lost information plays a major role, image inpainting has gained more importance. The inpainting term is copied from the ancient art of restoration technique for e.g. in museums. Removing unwanted object from an image and recreating them based on the spatial information of the neighbouring pixels i.e. filling the hole by using the information given from the nearby region of the same image which is done by using image inpainting (3). Applications of image inpainting are image editing, image restoration, font restoration, face restoration, removing unwanted object and much more (4).

The pioneer work of image inpainting presented in [5] which use partial differential equation that propagates information in the direction of isophotes. Image inpainting is divided into two types: Traditional techniques and deep learning techniques. Traditional techniques works either on diffusion based method that produce local structures into the missing parts or exemplar based method that fill the missing parts one pixel or patch at a time while protecting the consistency with the nearby pixels. In fact, natural images are complex, image information may include three parts such as shape or structure, texture that can be also regular or colour information.

2. Review Of Literature

2.1. Traditional Image Inpainting Techniques

Among well-talked traditional image inpainting algorithms; many which don't use deep learning methods will be discussed in this type.

2.1.1. Diffusion Based inpainting:

These techniques constitute pioneer approach is solving problems of image inpainting. These algorithms are relied on usage of variation method and the Partial Differential Equation (PDE). It filling the missing region by smoothly propagating content of image from visceral region into target region is the way work is done here (6). The algorithm uses the concepts of isophotes: curves of constant light intensity on surface (7). Main disadvantage is for the large missing regions it gives blurry result. Hence diffusion-based image inpainting approaches are more suited for comparatively smaller and non-textured regions.

2.1.2. Texture Synthesis Techniques:

This is one of the initial techniques of image inpainting. Patching is done and algorithms are then utilized for replacement of damaged pixel using likely surrounding to finish missing region. Structure of image is preserved by incorporating new image pixels from known region input. Patches from known images are copied and then reproduced to fill up missing region as similar patch for most of generic images doesn't exist (8). This technique gives genuine results for inpainting of small missing region of simple structure image. The procedure of filling is done in pixel style therefore this method is comparatively slow.

2.1.3. Exenplar Based Techniques:

It is also called Patch based image inpainting. This method is better than diffusion-based technique when it comes to fill large textured area. Within same patch it completes the absent part from the neighbouring pixels (9, 10).

2.1.4. Hierarchical Super Resolution Based Techniques:

Previous methods like exemplar-based method have faced problems such as patches filling order and size of patches. Here initially input image followed by hierarchical super resolution update is used to retrieve the more information of missing hole, because painting low resolution image is much easier than high resolution image (11).

2.1.5. Spatial Patch Bleanding Inpainting:

This is very quick and collective spatial patch blending technique. It can be embedded with all sort of pattern based inpainting algorithm. This can be used to minimise reconstruction artefact without changes to previously inpainted image (12).

2.2. Deep Learning Image Inpaintinhg Techniques

Deep learning inpainting algorithms have given more accurate solution to problem of image inpainting; looking into its far superior results. Contemporary researchers are more inclined to update, use or implement these new approaches.

Miniquin Wang et al [21] proposed a method which decomposes the texture image into carton image and texture image, then inpaints structure based on boundary restoration and use texture synthesis to inpaint texture image.

Deepak Pathak et al () [22] proposed a technique called context-encoder, which put in unsupervised feature learning operate by context based pixel prediction. The method is simple encoder-decoder, in that encoder brings out feature representation of the input image. Next, decoder gives this feature representation and generates the missing image content. They used reconstruction loss and adversarial loss function to handle both continuity within context and multiple modes in the output. Purpose of reconstruction loss is responsible for capturing entire structure of missing region and the consistency with the surrounding visible area and purpose of the adversarial loss make the real look for the output image.

Satoshi Lizuka et al () [23] presented both globally and locally compatible image accomplishment technique based on convolutional neural network for training. They used global and local context discriminators, global discriminators extract entire image as input and local discriminator takes only small area around the completed region to ensure both semantics of the restored image.

Guilin Liu et al () [24] utilized the incomplete convolutions for only valid pixels is cover up and reorganized. They designed Unet-like architecture, restoring all convolutional layers with partial convolutional layers and utilizing nearest neighbour up-sampling in the decoding stage. This method handles any shape size, or distance from the image borders and large hole size. The limitation of this method is they fail for some sparsely structured images.

Yanhong Zeng et al [25] presented Pyramid-context Encoder Network (PEN-Net). PEN-Net construct upon a U-Net formation, which acquired knowledge area from a high-level semantic feature map and convert visible area related features into low-level feature map. Also proposed a multi-scale decoder with deep supervision pyramid loss, this design results training converge quickly, also make the test more realistic.

Jingyuan Li et al [26] proposed a Progressive Reconstruction of Visual Structure (PRVS) network. Two VSR layers are utilized in the encoder and decoder stages respectively of U-Net like architecture to form the generator of a generative adversarial net (GAN). Apart from, partial-deconvolution is used in generator to solve the limitation of the partial convolution with existing modules. In the restoration process, partial convolution and bottleneck block are utilized to replace some edges in the missing region, and then the replaced edges are together with the input image with holes to slowly decrease the size of holes by filling important content and finally obtained fine image inpainting result.

Jingyuan Li et al [27] devise a Recurrent Feature Reason (RFR) network, built up by RFR module and Knowledge Consistent Attention (KCA) module. RFR module work by answer the simple part first and using that information to answer difficult parts, for inpainting first it concludes the hole border of the convolutional feature maps and then employ them as pointer for additional inference. Further, KCA module is progress to help the inference process of the RFR module. The KCA module is used to synthesize features by searching possible texture in the background and utilized them to restore textures in the holes, leading to better quality.

Convolutional neural network has not successful in explicitly copying information from distant spatial location, patch synthesis is suitable for that. Inspired by these **Jiahui Yu et al [28]** proposed deep generative model-based application which can not only combine novel image structure but also particularly work nearby image features as recommendation during network training compel finer prognosis. They proposed coarse-to-fine generative image inpainting with Contextual Attention Model (CAM), which improved results by learning feature representation for explicitly matching and attending to relevant background patches. They introduced two stage coarse and refinement networks, where first network for input build initial coarse prediction, and then refinement network using CAM refines this intermediate image to produce final inpainting result.

Zhaoyi Yan et al [29] introduced shift-connection layer to the U-Net architecture namely Shift-Net, which provides inpainting via deep feature rearrangement. For the approximation of the missing parts, distribute the encoder feature of the known region. A guidance loss is established to improve the explicit relation between the encoded features in the missing area. By utilizing such relation, the shift operation can be systematically worked and it gives better inpainting results.

Hongyu Li et al [30] proposed a deep generative model-based proposal which planed Coherent Semantic Attention (CSA) layer to study the relationship between features of missing area in inpainting. The consistency loss is established to improve the CSA layer learning capability for ground truth feature distribution and training steadiness. They used feature patch discriminator into model to gives better predictions. The model has two steps: rough inpainting which gives rough prediction and rough network is same as generative network and second step is refinement inpainting which predicts final result.

Min-cheol Sagong et al [31] presented Parallel Extended-decoder Path for Semantic Inpainting called PEPSI. This model has two stage networks feature encoding with single shred encoding network and coarse and inpainting paths which can decrease number of convolution operations undergo in parallel decoding network. The coarse path constructs rough result from the encoded feature map. Taking encoded features as an input and using refined features that constructed by the CAM generate high quality inpainting result.

Zili Yi et al [32] proposed Contextual Residual Aggregation (CRA) process in that from incidental patches create higher frequency residuals, that only need low-resolution divination from the network. They trained dummy on minor images with 512*512 resolution and carry out inference on excessive-resolution images which bigger than 1k. This process has the two stages coarse-to-fine network, where coarse network hallucinates rough missing content and the refine network predicts final results. To enhance computation efficiency, network designed in a slim deep fashion and Light Weight Gated Convolution (LW-GC) is trying for all layers of the generator.

Kamyar Nazeri et al [33] proposed EdgeConnect new deep learning model, which is divided into two stages edge generator and an image completion, both following an adversarial model. This representation initially predicts the image structure of the missing area in the form of edge maps. That edge map is used as previous information and the original image with mask is used as input of image completion network to get the repaired image.

Avisek Lairi et al [34] proposed Prior Guided GAN (PGG) model in which from the trained model damaged image correlated with noise is remove and then sent to generative model to recover the natural image. Increasing structural priors with noise priors to enhance GAN samples which results in better inpainting reconstructions also this model extended for video inpainting and concepts of structural priors.

Rolf Kohler et al [35] proposed an idea is to train a neural network to map corrupted image patches to their uncorrupted counterparts. This mapping is tried to all patches of a corrupted image. For getting the recovered image retrieved spots are averaged at their overlapping parts. It is also possible to blindly inpaint an image i.e. without knowing the location of the missing area by instructing an inpainting process for masks cause with definite fonts.

Raymond A. et al [36] proposed a method that creating the missing content by processing on the available data that done by semantic image inpainting with deep generative method. Given trained generative model, explore for the nearest encoding of the alter image in the multiple latent images using context and previous mislay. Encoding is forward through the generative method to infer the lost region. Missing content is structured in method, while learning based method need specific information about the holes in the teaching period.

Phillip Isola et al [37] proposed conditional adversarial network as a all-purpose solution to image-to-image movement difficulty, where this network easily adapt to the various structures of the missing regions. This network utilizes PathGAN to allow the discriminator to run differently from the traditional GAN that is works on patches rather than whole image. This network is successful at synthesizing photos from label maps, recovering object from edge maps and colorizing images.

Nermin Salem et al [38] proposed a face inpainting, which can represent and maintain the identity of human face in images using Histogram of Oriented Gradient (HOG) features as direction to the inpainting procedure. This technique has two stage networks, first face-shape predictor that recognizes human faces structure-preserving its local point i.e. eyes, mouth, nose. In second inpainting network from obtained information as prior, fills any random irregular missing areas. These networks use adversarial model for creating real image.

Huaming Liu et al [39] proposed image inpainting algorithm found on generative adversarial network. For filling the missing areas of the images this network use three factors such as content loss, gradient loss and prior loss. Content loss deal with the loss between created images and to be filled image in non-target areas, gradient loss deal with loss between created image and uncorrupted portions of the capture image, and prior loss deal with loss between filled image and real image. This method gives the features of training data and can semantically fill the missing regions.

Haoran xu et al [40] proposed general deep learning framework for high resolution image inpainting. This framework used for recovering of missing high-frequency information in High resolution (HR) image through a super- resolution (SR) enhancement mechanism. HR inpainting task divide into two stage, HR image inpainting technique and high-frequency information reconstruction technique. For inpainting first down sample the HR input into LR network and obtained inpainted result is used into SR mechanism for detail refinement, then inpainted HR outcome with high frequency details obtained.

Li Zhao et al [41] presented image inpainting technique based on generative adversarial network. This has two types: the generating network and discriminating network. The generating network created an image and discriminating network decide whether the image created by generating network compatible with real image. WGAN-GP loss function uses to determine the loss of parameters, in order to modernize the network alternately, constructing generating image more real.

Zhao Ruixia et al [42] proposed inpainting network based on GAN. This network used reconstruction and the generation path. In first stage, use the given real image and masked image to obtain its complementary image to reconstruct the original image, second stage generate the path and use the given masked image for inpainting. For decreasing gradient disappearance and gradient explosion problem, residual network is used in encoding and decoding process.

Haofeng Li et al [43] proposed Context- Aware Semantic Inpainting (CASI) method, which include convolutional architecture in generator conserve spatial structures and joint loss consist a perceptual loss to capture high level semantics around the synthesized region. They progress two new measures for evaluating sharpness and semantic validity, respectively.

Chao Yang et al [44] proposed semantic inpainting using multiresolution neural patch synthesis. This method preserves both structure and texture details. This method used following terms –

- Holistic content term – captures semantics and global structure of the image
- Local texture term – ensure that details in the missing hole are similar to the details outside of the hole, that produces sharper and more coherent results.

Ziwei Liu et al [45] proposed deep learning architecture for face features divination in the wild, which combine two CNNs, LNet and ANet. LNet locate the complete face region and ANet bring out high-level face presentation from the located area. Features learned in LNet are effectual for face localization and also differentiate between human faces and analogous patterns. Rough locations of face regions given by LNet, standard prediction of multiple patches can enhance the performance. They use massive objects and massive identities to pre-train LNet and ANet respectively.

Raymond A. Yeh et al [46] developed method using GAN for image restoration including image inpainting, colorization, super-resolution, denoising and inverse quantization. This method is based on the maximum a posterior (MAP) estimation. They re-establish the image by minimize a loss function and regularization term but rather of minimizing in the high dimensional image space, they work in the latent space explain by the GAN.

Jiahui Yu et al [47] presented free-form inpainting depend on generative network with gated convolution. Anywhere in the image with any shape, free-form mask may present, at that time global and local GANs planed for a only one rectangular mask are not appropriate. Therefore, they presented patch-based GAN loss called SN-PatchGAN. This applies spectral-normalized discriminator on heavy image patches. This method significantly enhances inpainting results with free-form mask and user guidance input.

Junyuan Xie et al [48] proposed image denoising and blind inpainting that collaborate sparse coding and deep neural networks pre-instruct with denoising auto-encoders (DA). Proposed method naturally eliminates complex patterns like super imposed text from an image alternately easy patterns like missing at random. In this method DA is used to perform pre-training because it naturally provide for denoising and inpainting tasks. DA has two-layer neural network that attempt to recreate the original input from noisy version of it.

There is a wide range of authors who used the technique and presented their discoveries, as can be found in Table 1.

Table.1. Summarize the traditional image inpainting techniques.

Author name	Technique used	Advantages	Disadvantages
Guillemot et al (3)	Diffusion based	Simple, useful for small size missing regions	Not useful for filling of textured regions, if large size missing region then result is blur
Kangshun Li et al (13)		Simple to execute	For complex structure regions gives blur result
Sumg Ha Kang et al (14)		Useful for large missing regions	Identifying feature point is hard

A. Levin et al (15)	Texture based	Perform fine on sharp corners and curves	Not useful in representing texture
Wallace Casaca et al (16)		Work well, Flexible	Unable to inpainting non-textured images with color variation
Alexander Wong et al (17)	Patch based	Useful for text, object and scratch removal, simple to execute	Useful for only small regions, work with grey images
J. Liu et al (18)		Useful for smooth objects	Unable to large size regions
M. Criminisis et al (19)		Preservation of edge sharpness, accuracy in synthesis of texture, speed efficiency	Does not handle curve structure and depth ambiguities
T. Ruzic et al (20)		Improve speed	Only for images not for videos
O. Le Meur et al (11)	Hierarchic-al super resolution	Simple, efficient and maintain context and texture in images	Does not work at curved structures, need high computation-al cost
M. Daisy et al (12)	Spatial patch blending inpainting	Work fast, useful for simple structure images	Unable to large size region, not useful for filling of textured regions

Table.2. Some deep learning inpainting techniques.

Author Name	**Advantages**	**Disadvantages**	**Dataset**
Miniquin Wang et al [21]	Inpaint texture image with complex structure	Fail for higher-resolution images	---
Deepak Pathak et al [22]	Performs well for centre square missing regions	Does not support random missing regions	ImageNet, Paris StreetView
Satoshi Lizuka et al [23]	Handle images of any sizes with arbitrary holes	Unable to handle complex structure, does not support random missing regions	Places2, ImageNet, CelebA, CMP Façade
Guilin Liu et al [24]	operate holes of any shape, size location or distance from the image edges	Cut out for some sparsely structured images, unable to handle largest of holes	ImageNet, Places2, CelebA-HQ

Yanhong Zeng et al [25]	Fills regions from high-level semantic features to low level features	Fail for higher resolution images	Façade, DTD, CelebA-HQ, Places2
Jingyuan Li et al [26]	Perform well on larger hole size	Does not work on higher-resolution	CelebA, Places2
Jingyuan Li et al [27]	Recover large continuous holes	Fail for higher-resolution	Places2, CelebA, Paris StreetView
Jiahui Yu et al [28]	Works on holes with different resolutions	Does not work on higher resolution	CelebA, CelebA-HQ, DTD, ImageNet, Places2
Zhaoyi Yan et al [29]	Effective in generating sharp structures and fine-detailed textured	Unable to low level vision tasks	Paris StreetView, Places
Hongyu Li et al [30]	Handle the discontinuity of the local pixels	Unable to style transfer and singe image super-resolution	CelebA, Places2, Paris StreetView
Min-cheol Sagong et al [31]	Reduce the operation time	Fail for higher-resolution	CelebA-HQ, Places2
Zili Yi et al [32]	Useful for ultra high-resolution images	Unable to image expansion, video inpainting and image blending	CelebA-HQ, DIV2C, Places2
Kamyar Nazeri et al [33]	Handle multiple, irregularly shaped missing regions	Fails for high-resolution inpainting	CelebA, CelebA-HQ, Places2, Paris StreetView
Avisek Lairi et al [34]	Better preservation of pose and size of object, gives 800x speedup, useful for video inpainting	Not suitable for natural videos or outdoor scenes	SVHN, Standford Cars, CelebA, CelebA-HQ, ImageNet
Rolf Kohler et al [35]	Mask-specific inpainting, blindly inpaint an image	Unable for large holes	Berkeley Segmentation
Raymond A. et al [36]	Works well for simple structures and large absent areas	Unable to handle complex structures	CelebA, Street View House Number (SVHN), StandFord Cars
Phillip Isola et al [37]	Effective at synthesizing photos from label maps, reconstructing objects from edge maps	Unable for video inpainting	Cityscapes, CMP Facades, ImageNet

Nermin Salem et al [38]	Preserve the identity of human face	Unable for high-resolution images	CelebA
Huaming Liu et al [39]	Maintain global consistency of structure and clarity of the local texture	Unable to fill arbitrary size and more complex scenes	CelebA
Haoran xu et al [40]	Useful for high-resolution images, handle both 2k and 4k images	Unable for video inpainting	DIV2K
Li Zhao et al [41]	Complete and clear structure, texture is natural and continuous	Fail for higher-resolution	Places2
Zhao Ruixia et al [42]	Texture is natural and continuous	Unable to higher-resolution	Places2
Haofeng Li et al [43]	Preserve spatial information, capture high-level semantics in the context	Does not restore a corrupted region with dense curved lines	CelebA, ImageNet
Chao Yang et al [44]	Works well on inconsistent holes	Added discontinuities and artifacts	ImageNet, Paris StreetView
Ziwei Liu et al [45]	Robust to background clutters and face	Does not handle higher-resolution inpainting	CelebA, LFWA
	variations		
Raymond A. Yeh et al [46]	Handle simple structures	Cannot handle general natural images	CelebA
Jiahui Yu et al [47]	Rapidly take out distracting objects, change image layouts, clear watermark, edit faces	Fail for higher-resolution images	Places2, CelebA-HQ
Junyuan Xie et al [48]	Handle low-level vision problem, automatically remove complex patterns	Unable to denoising and inpainting of audio and video	CelebA, Places2

3. DISCUSSION

In recent times, development in research and technology image inpainting has gained more importance. Motivation of image inpainting varies from aspect of image restoration, loss concealment, object removal and disocclusion. Context of application decides which algorithm to be used. Though very useful this technique has rendered failure in video inpainting objects in motion are difficult to track by this method but continuous advancement in image inpainting is trying to solve current issues.

4. CONCLUSION

Image inpainting is very important thing for computer vision application. As necessity of data modification using image, image feature enhancement, image restoration and other; importance of image inpainting has increased. In this paper image inpainting review is performed briefly. Traditional and deep learning approaches of image inpainting have been discussed in paper. Both type of technique has also been discussed in length. After this discussion we have concluded that no single method is best for inpainting all kind of distortions, but deep learning method gives very good results for every category that has been analysed. Though high computational complexity and high memory usage is still problem in deep learning method. Upcoming research should focus mainly on reducing the complexity of algorithms and ability to handle both simple and complex structure simultaneously.

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