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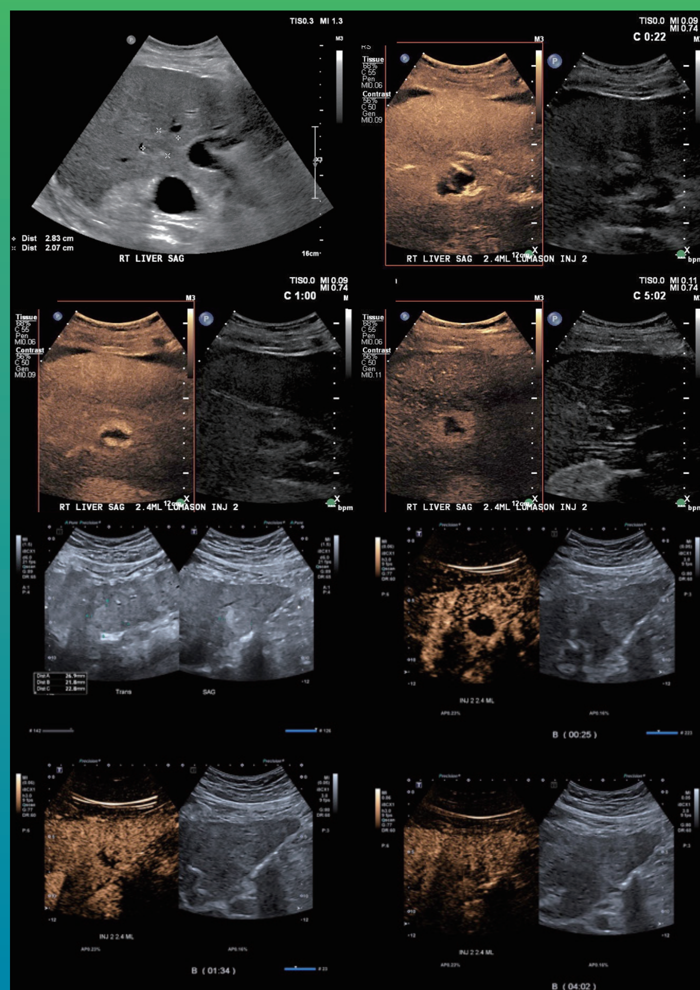

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REVIEW ARTICLE

Review on Image Inpainting using Intelligence Mining Techniques

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Objective: Inpainting is a technique for fixing or removing undesired areas of an image.

Methods: In present scenario, image plays a vital role in every aspect such as business images, satellite images, and medical images and so on.

Results and Conclusion: This paper presents a comprehensive review of past traditional image inpainting methods and the present state-of-the-art deep learning methods and also detailed the strengths and weaknesses of each to provide new insights in the field.

Key words: Image inpainting; Deep learning; CNN; Wavelet transformations

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Image inpainting is a process of reconstructing an incomplete image from the available information in a visually plausible way. While this procedure has traditionally been carried out by professional artists, it is now being used in the medical field, particularly in the field of medical imaging [1-3]. Medical imaging is a critical component of many diagnostic procedures. Image artifacts that are metal artifacts in Computer Tomography (CT) and Magnetic resonance imaging (MRI), limited field of view, selective reconstruction of recorded data, or superposition of foreign bodies in projection methods are all possible explanations for missing or partial image information in medical scans. It is obvious that missing visual data cannot be recovered in a diagnostic sense, implying that the data is lost [4-7]. However, correcting missing information inside medical scans is also of relevance for image post processing.

Medical diagnosis can be hampered by distorted medical images, particularly in the study of CT images and MRI. As a result, enhancing the accuracy of diagnostic imaging and recreating damaged sections is critical for medical diagnosis. These difficulties have recently received a lot of attention in the field of medical image inpainting. Local deformations in medical modalities are widespread due to numerous causes such as metallic implants, foreign objects, or specular reflections during image acquisitions; hence inpainting techniques are becoming more popular in medical image analysis [8-10]. Completing these missing or distorted regions is critical for improving post-processing tasks like segmentation and classification.

Interpolation, non-local means, diffusion techniques, and texture synthesis are all used in traditional medical image inpainting methods [11,12]. These traditional approaches are limited to a single image and do not learn from images with comparable properties. While these techniques can generate vibrant textures for background inpainting, they frequently fail to capture high-level semantics, resulting in non-realistic images with repeated patterns. We organize our review as: Section 2 presents image inpainting methods under different categories; Section 3 reviews traditional image inpainting techniques; Section 4 reviews deep learning techniques; Section 5 draws the conclusion.

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Image Inpainting Methods

There are few elements of image that break down each of the things a true artist should focus on, and they are line, shape, form, texture, pattern, color and space. Each brings its own unique quality to a picture. Inpainting techniques depend on the desired goal and type of image being treated. Treatments to fill in the gaps are very different between physical and digital art.

Physical inpainting

Inpainting is rooted in the restoration of painted images. It aims to make a visual improvement to the artwork as a whole by repairing missing or damaged parts using methods and materials equivalent to the original artist's work. The few points mentioned below are to be considered to inpaint any image: (1) The image as a whole determines how to fill in the gap; the purpose of inpainting is to restore the unity of the work so it is crucial to know how the repaired piece will function within the rest of the image; (2) The structure of the area surrounding the gap ought to be continued into the gap. Contour lines that end at the gap boundary are to be carried on into the gap; (3) The different regions inside a gap, as defined by the contour lines, are filled with colors matching those of its boundary although the specific materials do not have to be identical. If alternate materials are to be used, it is important to test for potential reactivity; (4) The small details are painted, i.e. “texture” is added to ensure the eye will not be drawn first to the in-painted region.

Digital inpainting

There are currently many programs in use that are able to reconstruct missing or damaged areas of digital photographs and videos. Given the various abilities of the digital camera and the digitization of old photos, inpainting has become an automatic process that can be performed on digital images.

More than mere scratch removal, the inpainting techniques can also be applied to object removal, text removal, and other automatic modifications of images and videos. Deep learning neural network based inpainting can be used for decensoring images. Three main groups of image inpainting algorithms can be: (1) Structural (or Geometric) Inpainting; (2) Texture Inpainting; (3) Combined Structural and Textural Inpainting.

All these inpainting methods have one thing in common: they use the information of the known or non-destroyed image areas in order to fill the gap, similar to how physical images are restored.

Structural (or Geometric) Inpainting Structural or geometric inpainting is used for smooth images that have strong, defined borders [13]. There are many different approaches to geometric inpainting, but they all stem from the same idea that geometry can be recovered from similar areas or domains. Bertalmio proposed a method of structural inpainting that mimics how conservators address painting restoration. Bertalmio proposed that by progressively transferring similar information from the borders of an inpainting domain inwards, the gap can be filled [14].

Textural Inpainting The structural/geometric inpainting works to repair smooth images but the textural inpainting works best with images that are heavily textured [15]. Texture has a repetitive pattern which means that a missing portion cannot be restored by continuing the level lines into the gap; level lines provide a complete, stable representation of an image [16]. To repair texture in an image, one can combine frequency and spatial domain information to fill in a selected area with a desired texture. This method, while the most simple and very effective, works well when selecting a texture to be in-painted. For a texture that covers a wider area or a larger frame one would have to go through the image segmenting the areas to be in-painted and selecting the corresponding textures from throughout the image; there are programs that can help find the corresponding areas that work in a similar way as 'find and replace' works in a word processor [17].

Combined Structural and Textural Inpainting Combined structural and textural inpainting approaches simultaneously try to perform texture- and structure-filling in regions of missing image information. Most parts of an image consist of texture and structure and the boundaries between image regions contain a large amount of structural information. This is the result when blending different textures together. That is why state of the art methods attempt to combine structural and textural inpainting.

Current image inpainting research mainly includes tasks with common Image Inpainting Applications such as repairing rectangular block mask, irregular mask, target removal, denoising, remove watermark, remove text, remove scratches, and coloring of old photos (Fig. 1). With all applications of inpainting, it is important to keep detailed records of the initial state of the images, treatments done and justification for treatment, and the original copies when applicable (e.g. original digital images).

Image inpainting experienced enormous amounts of research with considerable attention in the last few years, as researchers try to develop algorithms that are robust with less computational complexity. Various optimization techniques are proposed to enhance the capability of these algorithms to handle more complex image structures.

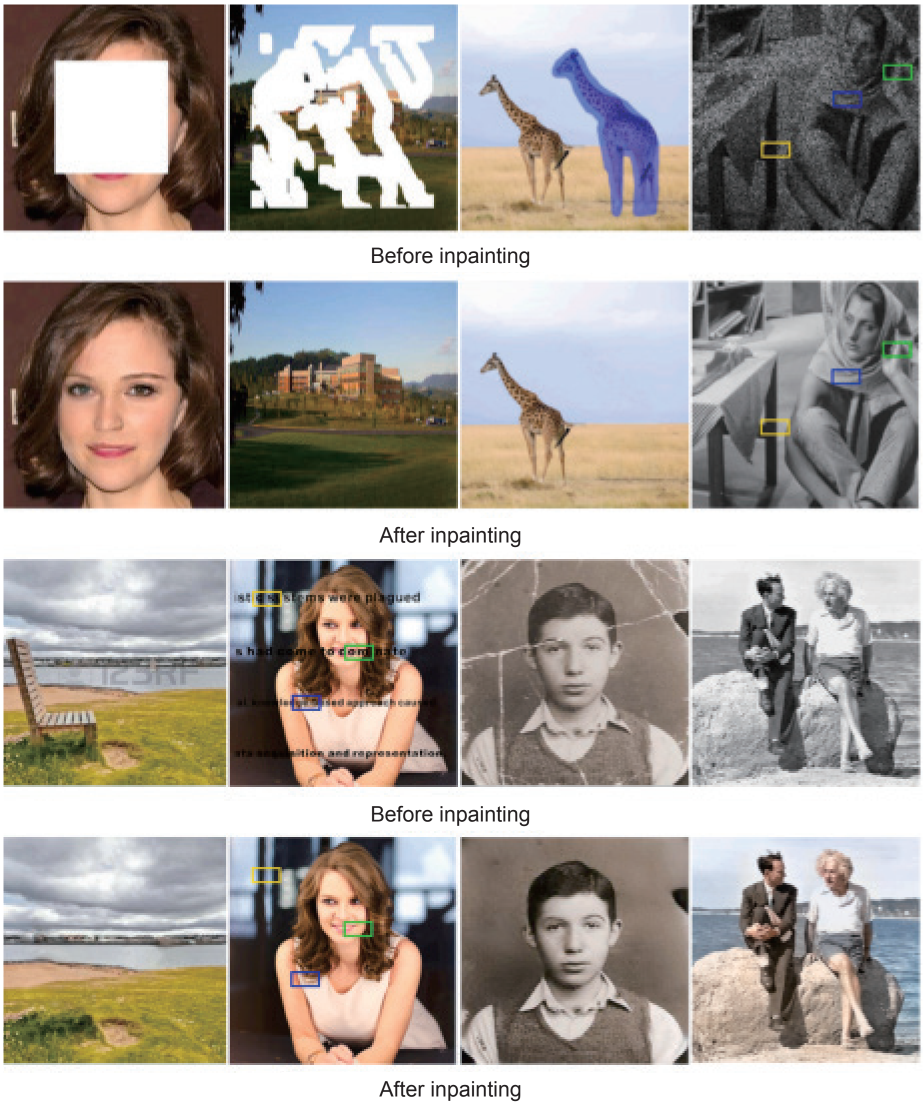

Figure 1 Common Image Inpainting Applications.

Traditional Image Inpainting Techniques

Image Inpainting originated from an ancient technique performed by artists to restore damaged paintings or photographs with small defects such as scratches, cracks, dust and spots to maintain its quality to as close to the original as possible. The classical image inpainting approaches also known as traditional approach or Non learning based approaches which do the inpainting process on the basis of certain algorithms and some of those inpainting techniques are discussed below:

Image restoration using inpainting

For an image restoration, images were recovered with CDD and TV inpainting technique. Images that are corrupted with noise are inpainted with the help of this method. It is applies with gray scale and RGB images.

Curvature driven diffusion CDD working is based on Partial Differential Equation of isophote for filling the missing region of images. Partial Differential Equation (PDE) based algorithm is proposed by Marcelo Bertalmio et al. [13].This algorithm is the iterative algorithm. The algorithm is to continue geometric and photometric information that arrives at the border of the occluded area into area itself. This is done by propagating the information in the direction of minimal change using isophote lines. This algorithm will produce good results if missed regions are small one. But when the missed regions are large this algorithm will take so long time and it will not produce good results.

Total Variation is a method used in images with different texture and the structures are filled with this texture inpainting. It collects the surrounding information to complete the image. Time required to inpaint images depends on size of images; it varies from few seconds to minutes to complete the image. The signal to noise ratio is compared [16].

Texture synthesis based image inpainting

The texture synthesis is a field of study independent from, but related to inpainting. In the general definition of this problem, an input sample of a texture is given, and the goal is to produce more of that texture. The simplest solution is to tile the texture sample on a rectangular grid of desired size. However, even if the sample can be tiled seamlessly, the resulting larger grid structure is easily noticeable and it distorts the perception of the actual texture. These algorithms have difficulty in handling natural images as they are composed of structures in form of edges. Hence while appreciating the use of texture synthesis techniques in inpainting, it is important to understand that these methods address only a small subset of inpainting issues and these methods are not suitable for a large objects.

Hybrid exemplar-based image inpainting algorithm

Image inpainting using exemplar algorithm is very popular technique in this area of inpainting. It works in two steps. First, it decides the order to fill the missing region. Second, it decides the good exemplar to fill this area. The problem with traditional exemplar technique is selection of suitable exemplar to recover image. For solving of this problem author provides modified technique with non-local total variation method. This method consists of two steps priority of patch and completion of patch [17]. First step is selection of Patch to complete the image based on the priority from the nearby area of target region. Secondly, complete the image with patch that found with maximum pixel matching with target region.

Digital image inpainting using patch priority based method

This algorithm is proposed for removing the object with larger size, the pixel value with maximum confidence and propagated into area to inpainted. Actual color is found using exemplar based inpainting. Previously texture synthesis algorithms are used which repeats two-dimensional pattern. The inpainting algorithm is design, which works linear structures [18].

Modified image exemplar-based inpainting

The image-inpainting algorithm is modified based on Exemplar technique. The focus of this algorithm is on patch priority. To fill the images with inpainted region here pixels maintains the confidence value. Pixel with confidence value and image isophote gives the priority. After finding the priority of pixel image divided into four parts. Then the image recovered with the pixel information available from surrounding [19]. The previous exemplar is unable to preserve the sharpness of images. However, this approach works well even the image is divided into segment.

Exemplar based image inpainting

Exemplar based inpainting algorithm with mean square method is designed. This algorithm consists of following outline:(1) Selection of target region by marking with some color. Author uses green color to mark image; (2) Then getting the area of target region; (3) Select the patch size of 9 × 9 size; (4) Finding the patch with maximum accuracy. Mean square error method defined here to find this patch. This method also called as normalized mean square error method. With this mean square error, method weight of pixel is found [20]. This weight act as priority for the pixel to fill the necessary information. This helps when more than one pixel with same information is found in nearby area; (5) Then the updating of patch is performed according to information obtained from previous step; (6) Finally, the patch is propagated into the inpainted region.

Wavelet transform based inpainting

The algorithm presented the technique with the help of the wavelet transform. Here we expect the best global structure estimation of damaged regions in addition to shape and texture properties. If we consider the fact of multi-resolution analysis, data separation, compaction along with the statistical properties, then we have to consider the wavelet transform due to its good image representation quality. Wavelet transform try to satisfy the human visual system (HVS). The algorithm decomposition of incomplete image is done with the help of wavelet and after that wavelet and scaling coefficients is found. The image inpainting process is applied in the wavelet domain by considering both scaling and wavelet coefficient from coarse to fine scales in the target region.

Semi-automatic and fast inpainting

The method by Jian et al. [17] proposed inpainting with Structure propagation. This performs two-step process. First a user manually specifies important missing information in the hole by sketching object boundaries from the known to the unknown region and then a patch based texture synthesis is used to generate the texture. The missing image patches are synthesized along the user specified curves by formulating the problem as a global optimization problem under various structural and consistency constraints. Simple dynamic programming can be used to derive the optimal answer if only a single curve is present. For multiple objects, the optimization is great deal, more difficult and approximated the answer by using belief propagation. This method discussed above take minutes to hours to complete depending on the size of inpainting area and hence making it unacceptable for interactive user applications.

Table 1 The advantages and disadvantages of the traditional inpainting techniques

Inpainting techniques	Advantages	Disadvantages
Image Restoration using Inpainting	Inpainted images with good resolution	More time is required for the computation
Texture Synthesis based Image Inpainting	Perform well in approximating textures	Difficulty in handling natural images
Hybrid Exemplar-Based Image Inpainting Algorithm	Produced good result for all digital images	If more than one pixel patch with same priority found then ambiguity is occurred
Digital Image Inpainting Using Patch Priority Based Method	Remove the large object and blur region	Not able to recover the satellite images
Modified Image Exemplar-Based Inpainting	Patch filling provides Speed efficiency, texture synthesis accuracy and propagation with maximum accuracy in linear structure	Slow, improvements needed in performance and video Inpainting
Object Removal Using Modified Directional Median Filtering For Digital Image Inpainting	Fast and simple algorithm is defined. The image recovered closely resemble with original image	Cannot used for non-homogenous images
Exemplar Based Image Inpainting	Patch founding is efficient to recover image	Extra computation time is required to find the patch and because of that, more time required for completion of image
Wavelet Transform based Inpainting	Utilizes inter and intra scale dependency to maintain image structure and texture quality using Wavelet Transform	Mask for regions are defined manually
Semi-Automatic Inpainting	Simple dynamic programming can be used to derive the optimal answer	Take minutes to hours to complete depending on the size of the Inpainting area
Fast Inpainting Technique	Takes less time to inpaint an image	Results in blur effect in image

Fast inpainting technique

To speed up the conventional image inpainting algorithms, new classes of fast inpainting techniques are being developed. Oliviera et al. proposed a fast digital inpainting technique based on an isotropic diffusion model which performs inpainting by repeatedly convolving the inpainting region with a diffusion kernel [18]. A new method which treats the missing regions as level sets and uses Fast Marching Method (FMM) to propagate image information has been proposed by Teleain [19]. These fast techniques are not suitable in filling large hole regions as they lack explicit methods to inpaint edge regions. This technique results in blur effect in image.

Image Inpainting Methods Based on Deep Learning

In all computer vision tasks, especially in image painting, the strong potential of deep convolutional neural 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 convolution 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 adversarial Networks (GAN).

Armanious et al. [16] suggested to use Generative Adversarial Networks in the inpainting of medical images. For the inpainting of missing information in a realistically detailed and contextually consistent manner, the proposed system comprises of two patch-based discriminator networks with extra style and perceptual losses. However, this method considers 2D images and utilizes fixed shaped masking in image and not considers irregular shaped masking. Also, there is need to avoid manual location of missing regions during training.

Liu et al. [17] used multi-resolution information to prioritize which target patches in an image is filled, which aids in determining the best image repair process. Similar patches are computed on multi-resolution images to obtain many candidate patches, and multi-resolution images provide more information than single-resolution images. To more correctly search for comparable patches, similar patch computations incorporate a range of information on colors, gradients, and borders. Using the structural similarity index, we identified the most reasonable candidate patch (SSIM). Graph cut technique was utilised to remove blockiness when pasting the patch to fill the target region. Although, approaches in this area are time demanding and exhaustive to create different candidate patches.

Li et al. [18] offered a PRVS (Progressive Reconstruction of Visual Structure) network that reconstructs structures and associated visual features in a step-by-step manner. Also, create a new Visual Structure Reconstruction (VSR) layer to connect reconstructions of the visual structure and visual feature, which benefit from sharing parameters.

In both the encoding and decoding stages of a U-Net-like architecture, repeatedly stack four VSR layers to construct the generator of a generative adversarial network for recovering images with tiny or large holes. However, learning structural elements takes time for the visual reconstruction layers, which increases the time it takes to filter out undesired structures that aren't essential for image reconstruction.

Li et al. [19] presented a plug-and-play Recurrent Feature Reasoning module and a Knowledge Consistent Attention module to build a Recurrent Feature Reasoning (RFR) network. The RFR module recurrently infers the whole boundaries of the convolution feature maps and then uses them as clues for further inference, similar to how humans solve puzzles. The whole centre limitations are gradually tightened by the module, and the effects become more visible. However, boundary artifacts have been developed due to discrepancies with feature maps.

Zhang et al. [20] developed a novel Consecutive Context Perceive Generative Adversarial Networks (CCPGAN) for serial section inpainting; this method extracts semantic information from adjacent photos and recovers the damaged areas of serial sectioning images to the greatest extent possible. Qualitative and quantitative results from two sets of serial sectioning photos of a mouse kidney revealed that method reliably recover breakage of any size and location while attaining near real-time performance. When the damaged patch becomes excessively large, there is a limitation because of minimal surrounding and much neighboring information employed.

Nguyen et al. [21], this work provided a fully automatic, unsupervised inpainting-based brain tumor segmentation system for T1-weighted MRI. To recreate missing healthy brain areas, a deep convolution neural network (DCNN) is first trained. After that, anomalous zones are identified by finding places with the highest reconstruction loss. Finally, such regions are segmented using super pixel segmentation. However, this method considers only square shaped masking and requires manual scaling of images.

Considers 2D images and utilize fixed shaped masking in image and not consider irregular shaped masking, time demanding as well as exhaustive and increases the time to filter out undesired structures, have boundary artifacts, and is not suitable for larger damaged patch and require manual scaling of images [16-21].

Researchers have continuously innovated and made great progress in generation model selection, network structure design, introduction of prior guidance, discriminator optimization, loss function optimization, etc. In this way, numbers of algorithms designed to recover the image but they are still lacking in some points to get recovery of image. Hence to solve the aforementioned issues, a novel solution has to be developed.

Conclusion

This paper provides an insight into different methods for image inpainting techniques used to recover the image or to complete the missing part of image by collecting information from the nearby area. Different methods for image inpainting like traditional image inpainting and deep learning-based image inpainting techniques are studied followed by its advantage and disadvantages are also discussed. The pixels with maximum priority are found by using different methods. Authors proposed number of methods that consists of partial differential based equation, exemplar based, wavelet transform, hybrid algorithm etc. Even though these algorithms provide good results than previous algorithms, still they are suffering with some drawbacks. So there is a need to define an efficient algorithm for filling the missing region of image. The algorithm should find the image patch that is closely resemblance with missing region of image, selection of size of pixel block and finally propagation of that patch into target region. All these steps need to be performed effectively so that recover image looks original to unknown user. While computing all these process, time is an important factor for which computation time must be less. In case of the quality of an image, blur should be removed and the missing region must be refilled inorder to make the reconstructed image as like original one. With consideration to limitations found, the images can be recovered with more accuracy and faster by using different algorithms further.

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Conflict of Interest

The authors have no conflict of interest to declare.

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