GLIMPSE OF IMAGE RESTORATION TECHNIQUE – IMAGE INPAINTING

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Abstract— Recent trends of digital photography and many other image editing applications posed another challenging problems to computer vision industry in demand. Inpainting is innovative technique for the modifying an image as visually plausible. There are numerous and very different approaches to tackle the inpainting problems. With this inpainting-based image coding solutions have recently emerged as a novel coding paradigm to further exploit the image visually plausible with good quality. In context to this we have present a survey on various image inpainting methods and their use and advantages and disadvantages.

Index Terms— examplar based, image inpainting, PDE based, restoration, texture synthesis, image completion.

I. INTRODUCTION

As computer vision industry is growing noteworthy nowadays and people are using many computer vision applications in them electronic gadgets. These all gadgets are of capable of procurement, processing, editing and storing these gorgeous types of content. With the advent of lots of multimedia instruments in nowadays peoples are become more photo centric and also trying to preserve their past pictures also. As the time goes on those pictures got damaged or they uses many application for editing images. So'Inpainting' is the art world's term in image processing which we can say as image restoration. Reconstruction of missing or damaged portions of images is an ancient practice used extensively in artwork restoration. Medieval artwork started to be renovate as earlyas the resurrection, the motives being often as much to bring medieval pictures 'up to date'as to fill in the gaps [1, 2]. In image restoration problem which is the form of image interpolation in which damaged area is filled by its neighborhood information. But the fundamental problem of image processing that what do we mean by images? Without knowing what images are, we could not hope to reconstruct missing data—this is the connection between inpainting and the fundamental problem of image processing. The objective of inpainting is to reconstitute the missing or damaged portions of the work, such as make it more legible and to restore its unity [3]. This field of research has been very active over recent years, and vigorous effort by numerous applications of image inpainting from reconstruction point of view are as follow:

- Missing data introduced during wireless transmission
- Removal of cracks, scratches, noise, dust
- Due to tightness marks on the scanned image
- Stamped date
- Red-eye from photographs
- The infamous 'airbrushing of political enemies [2]
- Object removal etc.

Before time way used by traditional restorators for filling the gap or removing the scratch, require more user interaction. Whereas the method used in [4] require less user interaction like the user selects an area for inpainting and algorithm automatically fills-in the region with information surrounding it which is visually plausible. The concept of Digital Inpainting was first introduced by Bertalmio *et al.* in 2000 [4]. One uniform color used by user for indicate the area they want to Inpaint. As image inpainting is an ill-posed inverse problem that has no well-defined inimitable solution [3]. To solve the problem, image priors are therefore necessary to introduce [3].

All methods used for inpainting are guided by the assumption that the same statistical properties or geometrical structures are shared by the pixels in the known and unknown parts of the image [3]. Due to this we can maintain goal of having an inpainted image as physically plausible and as visually pleasing as possible. The alteration of images digitally done such a way that its unrecognizable for an observer who does not know the original image cannot be identify that image is altered one or not. The fill-in is done in such a way that Isophote lines arriving at the regions' boundaries are completed inside. In digital technique of restoration user does not require to clarify from where information comes. As inpainting process is digitalized so it fill region automatically and speedy, thereby allowing to simultaneously fill-in numerous regions containing completely different structures and surrounding backgrounds. In addition, there are no boundaries put on the topology of the region to be inpainted [3].

In literature many earlier algorithms are based on PDE. Then general texture synthesis techniques were followed to synthesize texture along with structure. Patch-based techniques have been developed to increase the pace of process and for better simultaneous reconstruction of structure and texture. Recently, research has been done to better patch selection for exemplar based inpainting methods [6].

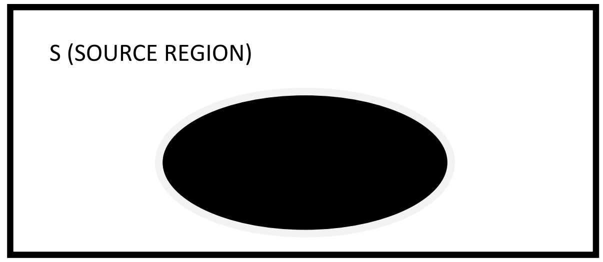

Fig. 2.1: Concept of Image Inpainting

II. IMAGE INPAINTING

An image **I** can be mathematically defined as:

$$i:\begin{cases}\Omega \in R^n \to R^m \\ x \to I(x)\end{cases} \quad (1)$$

Where **x** represents a vector indicating spatial coordinates of a pixel $p_{\mathbf{x}}$, which in the case of a two-dimensional (2-D) image (n = 2), is defined as $\mathbf{x} = (x, y)$. In the case of a color image, each pixel carries three color components (m = 3) defined in the (R, G, B) color space.

In the inpainting problem, the input image **I** (i.e., each color channel of the image) is assumed to have pass through a degradation operator, denoted **M**, which has removed samples from the image. so definition domain X of the input image **I** can be seen as composed of two parts: X = **S** and **U**, **S** being the known part of **I** (source region) and **U** the unknown part of **I,** which we search to estimate the color components of the pixels $p_{\mathbf{x}}$ located at each position **x** in the unknown region **U**, from the pixels located in **S** the known region, to finally construct the inpainted image which is as shown in Fig 2.1.

The recovered region looks natural to the human eye, and is as physically plausible as possible. Typical inpainting artifacts are unconnected edges, blur, or inconsistent pieces of texture (also called texture garbage) [3]. Here the uses uniform color to select the area to be inpainted by the methods so hole is created using this uniform color for digital inpainting.

III. LITERATURE SURVEY

Since digital inpainting was first introduced digital techniques are starting on large-scale for performing inpainting and numerous algorithms have been devised into the development of new and better digital techniques for inpainting. Almost all the algorithms do not require any user obtrusion. The only thing that user needs to specified is the area for inpainting. In different literature this area is termed as hole, fill region, occluded area, missing area, mask etc. Area which user want to be inpainted is usually selected using unvarying color. By studying overview of inpainting methods and content of [3] become to know various methods to restore the image such that it should not visually plausible. This section discusses various techniques with their basic ideas, pros and cons. The flow is maintained in a way they are upgraded for better results or year in which they were published or for this project as they read one by one. Discussion begins with different approaches which are categorized in basically two approaches as shown in Fig 3.1: A) Partial Differential Equation (PDE) based and B) Examplar based and Since various algorithms and techniques have been developed need to inspect every techniques for inpainting.

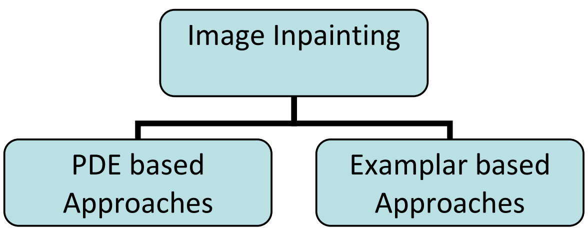

Fig. 3.1: Different approaches Of Image Inpainting

A. *Partial Differential Equation (PDE) based approaches:*

This section describes inpainting techniques which depend on either higher order partial differential equations or on variational approach. These concept can be formalized with PDEs, and diffusion is therefore performed using PDE-based methods. We can found many other methods exist using different models which tend toward the propagation in particular directions like linear, nonlinear, isotropic, or anisotropic or the curvature of the structure present in a local neighborhood needs to consider. Effective variants for completing straight lines, curves, and for inpainting small region. When circumstance created for propagating large texture, the upshot of blurriness these category of methods are not well suited. The term *diffusion* comes from the idea of propagating local information with smoothness constraints, by analogy with physical phenomena like heat propagation in physical structures [3].

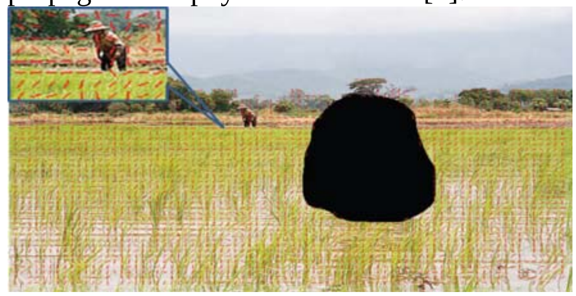

Fig. 3.2: Isophote or lines (in red) of constant intensity represented for one out of ten pixels with a zoom on one region of the image [3].

For propagation inpainting uses diffusion which propagating smoothly local image structures from the exterior to the interior of the hole. Moreover, directions must follow by it which are given by local image structure for preserving edges, the regularization (or smoothing). The first step is therefore to retrieve the local image geometry. After that use PDEs or variational methods to describe continuous evolutions of the image and of its structures. By computing gray level lines (also called *Isophote*) or structure tensors Local image geometry can be retrieved [3].

Bertalmio *et al.* [4] has prepare new way for the restorers and pathfinder of digital image inpainting in 2000. The basic idea they presented was to continue information arriving at the boundary of the occluded area. Geometric and photometric information are extended in occluded area to do the same. This information is acquired through continuation of 'Isophote' (As shown in Fig 3.2) lines [4]. Isophote lines are the lines of direction of minimal change in intensities. For conserving the direction of Isophote lines, the image information is propagate inside the hole such as take care of direction of Isophote lines. Algorithm produces good results for comparatively small holes because of algorithm at the same time fill multiple occluded areas. The main drawback of this algorithm was reproduction of large texture regions [4]. Thus this approach is not suited for large holes and sharp edges. Further, number of iterations required to fill in whole area is large which results into longer time of execution as shown in Fig 3.3.

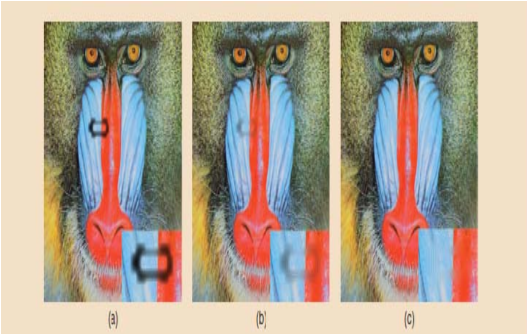

Fig. 3.3: The diffusion process with isotropic diffusion after (a) ten, (b) 20, and (c) 600 iterations [3].

Later, Chan and Shen [7] devised mathematical models for non-texture inpainting. This method used second order PDE model. This model was devised from Rudin-Osher-Fatemi's total variation restoration model [8]. This model was called Total Variation (TV) model and followed all three inpainting principles described in [7] as A) being local; B)the capability of being restore the broken edges; C)robustness to noise. They also show connection of inpainting with digital zoom in process and image decoding and compression. Curvature Driven Diffusion (CDD) method proposed by the same authors due TV model suffered from connectivity problem as shown in Fig 3.4 which was overcome by CDD method and CDD model used third order PDE model. This model helped in preventing smooth areas from becoming too blurred. Moreover, it had the ability to denoise inpainting region noisy regions. The major drawback of this technique is, again, inability to restore textured region and CDD model do not show remarkable good result on large curvature. In depth overview of variational models are described well by Chan and Shen [9].

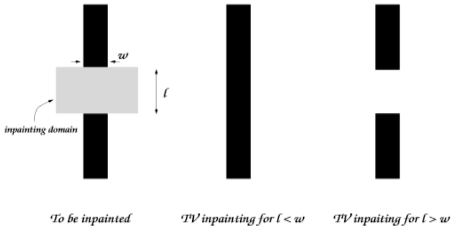

Fig. 3.4: Major drawback of TV model [9].

For improving the result of PDE based techniques some researchers tried for texture synthesis and PDE based methods for inpainting proposed by Bugeau and Bertalmio [10]. However, still this method also gives some blurriness as they depend on diffusion method.

Now here shown comparison of all methods in Table 3.1 which all methods discuss here in this section. Methods Used For PDE Based Inpainting Approaches in this paper.

Table 3.1 COMPARISION OF ALL METHODS OF PDE BASED APPROCHES

Features	**Bertalmio[4]**	**Chan and Shen[7]**	**Chan and Shen[9]**	**Bugeau and Bertalmio [10]**
Order of PDE	2^{nd}	3^{rd}	3^{rd}	Using tailor series derived 3^{rd}
Model Used	Anisotropic	Linear and Orthogonal	Linear and Curvature	Anisotropic
Gap	Small	Small	Small	Medium to large
Tensors used	Isophote	-	-	Structural
smoothness	No	No	Medium	Medium
burliness	Yes	Yes	Medium	Medium
Curvature	No	No	Yes	Yes
Edges preserve	No	Yes	Yes	Yes

B. Examplar based Approaches:

Other members of this image inpainting methods are Examplar based methods which overcome drawbacks of other previous one and recent most of the work going on Examplar based methods. In the category of literature there are many researchers had work on these approaches. Examplar-based inpainting has been, for a large regions, local region-growing methods which propagates the texture one pixel or one patch at a time the flow as shown in Fig 3.5, while maintaining relevancy with nearby pixels as shown in Fig 3.6.

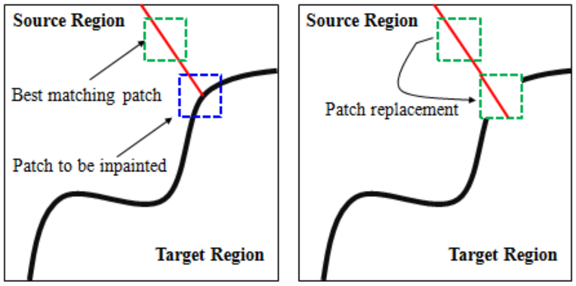

Fig. 3.5: Flow of Exemplar based inpainting algorithm [6].

The exemplar based image inpainting consists of the following steps:

- Initializing the Target Region: In this step find the patch to be inpainted.
- Computing Filling Priorities: In this a using priority function compute the filling order for all patches.
- Searching Example: In this the most similar and best pattern is found from the source area to compose the given patch, which centered on the given pixel.
- Updating Image Information: In this the boundary of the target area and the necessary information for computing filling priorities for the exemplar based image Inpainting are Updating.

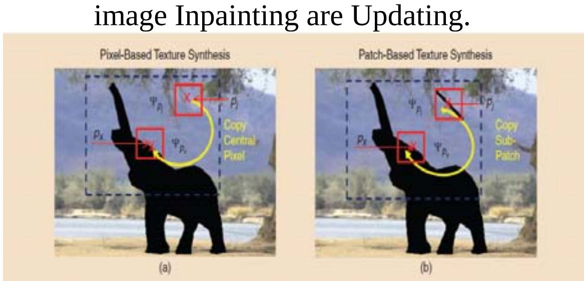

Fig. 3.6: The principle of Examplar-based methods: search for the patch the most similar to the known part of the input patch to be completed (a) pixel-based approaches or (b) a set of pixels for patch-based approaches [3].

Similar regions in a texture sample or from the known part of the image the texture composition is learned. Learning is done by sampling, and by copying or stitching together patches (called *examplar*) taken from the known part of the image. The corresponding methods are known as examplar-based techniques. These methods are faster than pixel based approaches. For optimize patch-based methods many variants have then been introduced and they as follows:

- Distance metrics for finding best matching patches.
- Fast search of best matching patches.
- Patch processing order.
- Patch stitching with blending and quilting.
- Methods to learn unknown pixels from best matching patches.

Generally it's shown that Image may be composition of structure and texture both. For the applications like removal of the objects it's necessary that after selecting the object for removal its needs to complete the structure. Criminisi *et al.* [12], in which processing order is highly dependent on the order of filling. The processing order is given by a patch priority measure defined as the product of two terms ($P(p_x) = C(p_x) \times D(p_x)$). The first term accounts for the amount of known pixels versus unknowns in the input patch which is a so-called confidence Term $C(p_x)$ and the second term $D(p_x)$, called data term, and reflects the presence of some structure in the patch. Proposed method [12] is capable of propagating linier structure and 2-D texture. Methods discuss here falling under the category of patch processing order. This method has drawback that it cannot handle depth ambiguities and not gives proper result for curved structures.

Other method proposed by Drori *et al.* [13] that completing the missing part caused by removal of foreground and background elements from the image. The approach progress patch per patch in a greedy fashion; for this reason, they do not ensure a global image relevancy. Using the iterative process proposed method[13] smoothly reconstruct image by image fragments which require training data set and completion of image done by principles of figural simplicity and figural familiarity. This method is matching based method and they work as explicitly match patches in the unknown region which be filled with those in the known region and then copy them. Somehow use greedy fashion. Some guidance from course to fine levels for the missing regions are iteratively approximated .Try to fill the region by using the example fragments [13].Method in [13] does not handle ambiguities in which the missing area covers the intersection of two perpendicular regions. Also does not differentiate between figure and ground. This shows a limitation for completion when the inverse matte is on the boundary of a figure, since both the figure and background can be synthesized by example.

A Wong and J Orchard proposed method using non locals means or information [14] for inpainting. Using the nonlocal image information from multiple samples within the image and recover the gap using weighted similarity function and aggregated to from the missing information and improved the visual quality .From the study we found that example-based methods exploit redundancy in natural images for filling missing pixels. Geometrical rearrangement of image includes several operations and method [15] describes optimal graph labeling where selected label for every pixels are represented by shift-map. Graph labeling done using the graph cuts. Uses the hierarchical optimization for fast calculation though this method is fail in propagating the large texture. As describe in [15] as global optimization is use for various geometric rearrangement problems. Proposed method combines several desired properties [15]:

- For accurate object selection minimal and intuitive user interaction.
- The global smoothness term minimized by.
- The geometric structure of the image is preserved.

As discuss ahead that structures and texture are consider differently. So such other method which use the same fundamental by S. Li and M. Zhao [16]. This method Inpaint using the salient structure completion and texture propagation. For that extract the salient structure by wevlate transform and detect the color texture and curvature feature around the salient structure. In second step complete the structure and then texture will be propagating such way that first complete the structure and then texture will propagate in residual region. When structure is too complex (edges) then this method fails to complete the structure and also it find difficulties when texture are too similar pattern.

Using the statistics of the patch methods discuss in [17] complete the images. This method is efficient enough to complete the complex structure also. The whole algorithm follow the following steps to complete the image. (i) Matching similar patches (ii) computing offsets statistics (iii) filling the hole by combining shifted images. They find the similarity measured by sum of squared differences (SSD) between two patches. After all this compute the coherence measure and it found too small. So which indicate that this method is efficient. Though the method has advantages but when desired offset not found then this methods lead to failure cases.

How quickly the image inpainting algorithms can find the patch using the random search and propagate the patch that discuss in [18] by C. Barnes *et al.* This method find the matching patch using the nearest neighbor search using the random sampling and coherence allows to propagate it. In this work they compare kd-trees with dimensionality reduction by speed and memory usage of them algorithm, and show that it is at least an order of magnitude faster than the best competing combination (ANN+PCA) and uses significantly less memory [18]. Sometime this method lead to unusual results.

K. He and J. Sun [19] show that how to find the nearest neighbor fields via propagation assisted KD-trees to quickly find the approximate solution. Proposed method [19] is faster and accurate than [18].Using the KD tree not only reduce the time but finds accurate patches also. But mention method is not generalized for search process.

Whereas Guillemot *et al.* [22] shows that low-dimensional neighborhood representation (LLE-LDNR).The inpainting algorithm first searches the K-Nearest neighbors (K-NN) of the input patch to be filled-in and linearly combine them with LLE-LDNR to synthesize the missing pixels. Linear regression is then introduced for improving the K-NN search. The improved-NN search by using subspace mapping functions learned with linear regression (LR) from patches in the known part of the image. The LR (linear regression) is also considered for estimating the unknown pixels [22].

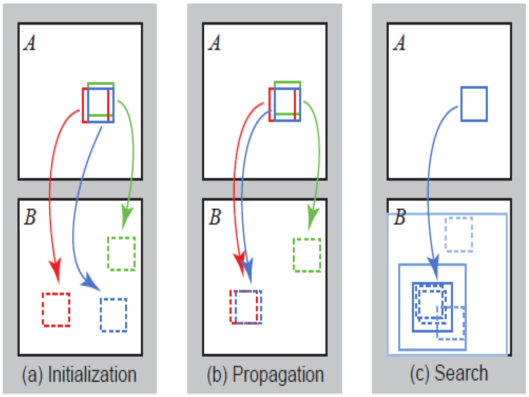

Fig. 3.7: Phases of the randomized nearest neighbor algorithm [18].

As discuss earlier that in some literature they used statistics of the images to complete the image. And in literature there are two type of statistics: A) Internal statistics and B) External statistics.as internal statistics have lower memory and computational demand they are more powerful than global statistics. They compare this statistics based on two parameters as expressiveness and predictive power [20].Compact representation of patches cannot capture well full rich of statistics and this open doors for more powerful priors.

Methods introduced by A. Levin *et al.* [21] that uses the global or external statistics of the images and this problem from the context of statistical learning. Based on the histograms of local features given method [21] training image build an exponential family distribution over images. For Inpaint the hole of this image specific distribution them finding the most probable image given the boundary and the distribution. The optimization is done using loopy belief propagation. As shown in literature for capture the "look" of an image using model based on histograms of local features and shown that how to filling hole and how these histograms use. This method is adopt by [17]. N.Komodakis [23] has given well defined objective function for solving the problem of optimization and that scheme called "belief propagation". In [20] illustrated using the internal statistics of the images they show that by using the internal statistics of the images we get the advantages of low computational cost and it consume less memory.

Other technique C. Tang *et al.* [25] that source and sample images use for extracting structural information and then constrains used that boundary band map and contour consistency to perform template matching for reconstruct the damaged structures. After this weighted exemplar-based image synthesis algorithm used to take previous structural information and matching results into account. Limitation we found in [25] that sample image necessary for complete the structure in most of the cases so cannot use for object removal application and propagation because in this type of work there is no sample image given to system.

Jia-Bin *et al.* [28] propose a method for automatically guiding patch-based image completion using mid-level structural cues. This method first estimates planar projection parameters, softly segments the known region into planes, and discovers translational regularity within these planes. This information is then converted into soft constraints for the low-level completion algorithm by defining prior probabilities for patch offsets and transformations. This method fail to detect vanishing points or plane regularities [28].

Some of the authors have also proposed hybrid methods which uses both the approaches. Diffusion methods work well for small and sparsely distributed gaps. They are also appropriate for piecewise smooth images and for propagating strong structures. But they are unable to restore texture. On the contrary, examplar-based methods work amazingly well in textured regions with homogeneous or regular patterns. Nevertheless, they are not so well suited for preserving edges or structures, or for images with many small distributed holes. Yet, natural images contain composite structures and textures. These category of methods also not given good results for occluded objects. For the curvature of large hole still not well suited methods. The structures constitute primal sketches of an image (e.g., edges, corners) and textures are regions with homogenous patterns or feature statistics. To handle composite textures and structures, it is therefore natural to combine different types of approaches [4].

Two main strategies have been considered. The first strategy consists in first separating the image components texture and structure from the source image, and inpainting them separately with the most suitable method for individual aspect (e.g., diffusion or examplar-based). The two inpainted components are then added together as in [27], [28]. A second strategy consists in combining different approaches in one unique energy function using a variational formulation [12], [25]. But it's very difficult at run time to decide which structure and texture are inpainted using which appropriate methods. So if uses these type of strategy then time taken for inpainting is big constrain. These all things leads us towards the concept of fast inpainting or semi-automatic inpainting methods. M.G.Padalkar *et al.* [30] proposed approach for automatic detecting the demaged region or hole for the inpainting using SVD based technique. They proposed this technique for heritage place. But when dissimilar patches are matched and input mast need to select well suitable and threshold values also then method shows failure.

C. Comparison of All Approaches:

This section describes the feature based comparison of all the methods as shown in blow table 3.2:

Table 3.2 FEATURE BASED COMPARISSION OF ALL INPAINTING METHODS [3]

Features	**PDE-based Diffusion**	**Examplar-based inpainting**	**Hybrid methods**
Priors	Smoothness	Self Similarity Sparsity	Smoothness + Similarity/ Sparsity
Optimization	Greedy	Greedy or Global	Greedy or Global
Sensitivity to Setting	Low	High	High
Holes	Small	Medium to big	Medium to big
Applications	Restoration	Restoration, Editing, Disocclusion, Concealment	Restoration, Editing, Disocclusion, Concealment

IV. CONCLUSION

We studied different methods of Image Inpainting and variants of each approaches. Image inpainting is the technique which use in many ways in the computer vision and image and video editing tools. We can have other more application based on image inpainting using another methods and tools. Image inpainting algorithms can be used on images as well for video also.

We have shown on various image inpainting techniques and advantages and disadvantages of them. As discuss ahead many computer vision application we can be develop using image inpainting techniques with other variations. Still this is the open research area for computer vision for images as well as video. Many algorithms are proposed for image inpainting for video and image but they running times needs to be minimized. Still many algorithms does not gives good result for occluded objects as the image itself a 3D.so algorithms needs to be improved as running time and must give result as visually plausible.

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