1.Title: HIERARCHICAL DIGITAL IMAGE INPAINTING USING WAVELETS.

Majority of the Image Inpainting Algorithms achieve such a task by using Partial Differential Equations. The applications of inpainting includes reconstruction of small damaged paintings, removal of superimposed text, removal of scratches due to folding of images, removal of an object in an image etc. Many graphics editing softwares have incorporated a tool for inpainting. The difference between these tools and the inpainting algorithm which we follow is that, the former requires the user to select both the region to be inpainted and the pattern that is to be filled in the unknown region. Hence it creates overhead on the user as he/she may not be sure of the exact pattern to be used to fill while the latter takes only the region to be inpainted as input from the user. The result of the tools will have blocky effects when it just replaces the original region with the new pattern. Moreover the process becomes tedious when the user has to fill large number of smaller areas.

The process of inpainting, as mentioned in the Fig.1 includes masking out the unknown region selected by the user, and the inpainting technique is applied to fill the masked region. Many inpainting techniques have been proposed which retouches the image in an effective manner. Some of the existing techniques are interpolation, isophotic diffusion and exemplar based inpainting. Interpolation and diffusion based techniques work well for smaller areas but fails to reproduce texture properly. It also results in blurring of edges. Whereas exemplar based method works well for larger areas but fails in proper reproduction of definite shapes. It results in excessive propagation of texture and hence damaging the larger structures in the image. In this paper, the structure and texture information are separated and the coarser structures are handled first and then moving to finer details. Multi resolution property of the wavelets makes it desirable to be used in the process of inpainting. As the wavelets has the property of separating the low pass and high pass coefficients, it provides us the structure and texture information of the image. Inpainting algorithm is applied to four subbands of the image formed after applying Wavelet Transform. This gives a better reconstruction of the images.

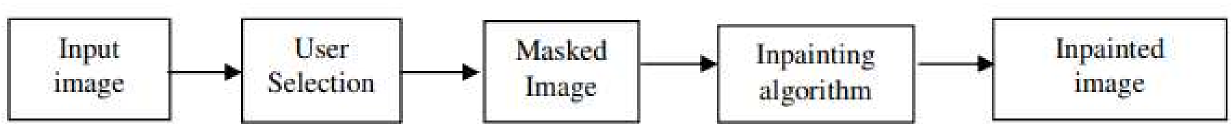

Figure 1. Inpainting Process

The hierarchical method tries to keep the mask size smaller while wavelets help in handling the high pass structure information and low pass texture information separately. The performance of the proposed algorithm is tested using different factors. The results of our algorithm are compared with existing methods such as interpolation, diffusion and exemplar techniques.

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2.Title: IMAGE INPAINTING VIA SPARSE REPRESENTATION.

Generally speaking, there are two main categories of image inpainting approaches in the literature: PDE based approaches [2,18] and exemplar based approaches. The formers aim to extend the lines or edges in known area into the user specified areas, which pay sufficient attention to structure propagation, but do not suitably deal with large regions due to the blur effects in their case. The later approaches [8,9] adopt texture synthesis method to synthesize the pixels in the user specified region. For a particular target patch, they search the most suitable source patch from remaining regions to replace the target patch. Later, [6] considers the structure propagation as well as texture synthesis by computing patch priorities for determining the filling order. Their improvements [3, 13] have also been proposed by some researchers. Some others also pay attention to both texture and structure propagations. Sketch model [11] has been used to restore the missing structure, and then patch based synthesis is deployed to fill in the regions [5]. Similar works in [10, 16] use PDE based method and tensor voting, respectively, to restore the structure, and then deploy texture synthesis to fill the specified regions. Works in [17] allow user to manually specify important missing structure information, and then deploy dynamic programming or belief propagation to complete the structure before synthesizing the pixels in target regions. Generally speaking, exemplar based approaches work well to synthesize the texture in target areas, thus are more suitable to deal with large regions, e.g. to remove background persons in a photograph, and to keep image details in the filled region. However, it always selects the most suitable patch for the current place, thus is a greedy method, which results in a risk of introducing unwanted object or artifact to the area to inpaint, which can be seen in the bottom right images in figure2 (a) and (b). As we will point out, this inpainting method can be viewed as a special case of our proposed algorithm here, and the general cases of our methods are less greedy. Our main contribution is to borrow the signal sparse representation technique to address the inpainting problem, and bridging the gap between sparse representation and texture synthesis. Signal sparse representation means that the signal admits a sparse representation over a redundant dictionary, which we will review in the following section. In this paper, we view this problem as the recovery of incomplete image signals, with each signal corresponding to a patch. We fill the hole patch wisely based on the sparse representation of each patch. The rest part of this paper is organized as follows. In the second section, we simply review the used sparse representation technique: Lasso. In the third section, we describe our inpainting algorithm. The experimental results are listed in section four. Finally, we discuss the relation between the proposed algorithm and some related issues, and then we conclude this paper.

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3.Title:Image Restoration using Multiresolution Texture Synthesis and Image Inpainting.

Restoration in this context refers to removal of image defects such as scratches and blotches as well as to removal of disturbing objects as, for instance, subtitles, logos, wires, and microphones. Our method combines techniques from texture synthesis and image inpainting, bridging the gap between these two approaches that have recently attracted strong research in terest. Combining image inpainting and texture synthesis in a multiresolution approach gives us the best of both worlds and enables us to overcome the limitations of each of those individual approaches. The restored images obtained with our method look plau sible in general and surprisingly good in some cases. This is demonstrated for a variety of input images that exhibit different kinds of defect.Today, digital photo cameras have established them selves on both consumer and professional markets. Apart from the immediate availability of photos for viewing and/or electronic transfer to an editorial office, digital cam eras have the big advantage of producing electronic images that can easily be stored and copied without loss of quality for the next decades to come. Although these advantages may sound great, one has to consider that the number of analog camera sales worldwide each year is still a multi ple of the number of corresponding digital camera sales: the quality and resolution of analog images is still hard to achieve even for high-end (and high-price) digital cameras. As a result, the amount of analog images that have to be digitized in order to "live forever" is still growing. In addi tion, many photographs from the pre-digital era still need to be digitized to prevent them from decay. Unfortunately, this material often exhibits defects such as scratches or blotches. Equally disturbing artifacts are, for instance, subtitles, lo gos, and physical objects such as wires and microphones, which should be removed from the image. Obviously, it is desirable to remove defects or disturbing objects in a fully automatic way. Such automatism would include detection of the image regions to be repaired as well. Although an automatic detection should be possible for obvious defects, the detection of unwanted objects is a completely subjec tive process that cannot be performed without user interac tion. Due to this restriction, and to avoid going beyond the scope of this paper, we do not address automatic detection here. For the special case of image sequences, detection and restoration of image defects has been addressed in [14]. In this paper we present a new method to automati cally repair "damaged" areas of digitized photographs. Our method performs a frequency decomposition of the input image to combine techniques and ideas from two different areas of research: texture synthesis and image inpainting. Recently, texture synthesis [9, 19] has become an ac tive area of research. The common idea of all texture syn thesis approaches is to create a new texture from a (typ ically small) initial seed texture such that the appearance (i.e. structure and color) of the synthesized texture resem bles the sample texture. Early approaches employed image pyramids and histogram matching to create two- or three dimensional textures from a 2-D sample image [11], or syn thesized textures by sampling successive spatial frequency bands from an input texture, which has been decomposed using a Laplacian pyramid [7]. Texture synthesis based on statistical measurements of the seed image and its wavelet decomposition has been proposed in [17]. The approach presented in [10] is based on the original work in [9] and introduces a scheme to select the order of pixels that are synthesized. Recent publications focus on texture synthesis on surfaces [20, 18, 21], texture synthesis for “natural tex tures” [2], real-time texture synthesis [15, 22], or on texture transfer [8, 12].

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4.Title: A Review on Image Inpainting Techniques and Datasets.

Digital image inpainting techniques are classified in traditional techniques and Deep Learning techniques. Traditional techniques are able to produce accurate high-quality results when the missing areas are small, however none of them are able to generate novel objects not found in the source image neither to produce semantically consistent results. Deep Learning techniques have greatly improved the quality on image inpainting delivering promising results by generating semantic hole filling and novel objects not found in the original image. However, there is still a lot of room for improvement, specially on arbitrary image sizes, arbitrary masks, high resolution texture synthesis, reduction of computation resources and reduction of training time. This work classifies and orders chronologically the most prominent techniques, providing an overall explanation on its operation. It presents, as well, the most used datasets and evaluation metrics across all the works reviewed. Inpainting started to be applied, as early as the Renaissance [1], in the restoration of damaged painted images, due to aging, scratching or other factors. Physical inpainting is a very time consuming process as it’s manually carried by skilled art conservators or restorers to reconstruct valuable paintings and conserve its cultural heritage, using any methods that prove effective in keeping it as close to its original condition. With the arrival of photography and film, the need to reconstruct media extended, giving birth to digital inpainting. This type of inpainting addresses the same issues as physical inpainting, plus the ones added by digital image corruption. Digital inpainting is a process that focus on the application of sophisticated algorithms to reconstruct digital image data. Currently it is used for many applications such as, image editing, coding, restoration, removal or replacement of objects, film and television special effect production, robot vision, etc.

References:

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5.Title: Image Inpaint Using Patch Sparsity.

In this algorithm is proposed for removing objects from digital image. The challenge is to fill in the hole that is left behind in a visually plausible way. We first note that patch sparsity based synthesis contains the essential process required to replicate both texture and structure the success of structure propagation however is highly dependent on the order in which the filling proceeds. We propose a best algorithm in which the confidence in the synthesized pixel values is propagated in a manner similar to the propagation of information in inpainting.The actual color values are computed using patch sparsity based synthesis. In this paper the simultaneous propagation of texture and structure information is achieved by a single, efficient algorithm. For best results selected image should have sufficient background information. Image inpainting is an interesting topic in computer graphics and an active area in research in image processing. Image inpainting is also known as image interpolation or completion. Object removal from image is an image manipulation technique that has a long history and the purpose of removing objects varies from removing undesired object to improve the quality of the image , to airbrushing out political enemies from portraits of important events. Modern photographical manipulations, such as red eye removal from pictures, also utilized this technique. It is used in video inpainting also to correct videos. The purpose of inpainting is to filling in the missing part of an image . Diffusion based inpainting preserves the structure (i.e. lines and object contours) by propagating the isophote (a line of equal luminance) in the unknown region . By construction this approach achieves excellent results when the missing region is small. This problem occurs when block of data have been lost in transmission [1], or intentionally pruned for compression, or when an unwanted object has to be removed. In this context the missing part contains both image structure and texture . State of art methods are patch sparsity based inpainting and were inspired by texture synthesis algorithms.Inpainting using patch sparsity fills the holes in an image by searching similar information on the known region in terms of patch and simply copies it to the unknown region as is done in texture synthesis. The previous idea is based on the fact that natural images contain redundant or very similar information. Greedy inpainting using exemplars also known as patches consist of two major steps select the patch to be filled and propagate the texture and structure. The former step selects patches with mostly linear structures by giving them higher priority. The later is related to the selection of the most similar patches from which the information is copied. These two steps are iterated until the holes in the image are fully restored.Image inpainting applications are in repairing photographs to remove unwanted objects. This may be used in producing special effect in images and videos .

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[2] Antonio Criminisi, Patrick Perez, and Kentaro Toyama "Region Filling and Object Removal by Exemplar Based Image Inpainting" in IEEE Transactions on Image processing, vol. 13, no. 9, September 2004 .

6.Title: Image Filling By Using Texture Synthesis.

A new algorithm is proposed for removing large objects from digital images. The challenge is to fill in the hole that is left behind in a visually plausible way. In the past, this problem has been addressed by two classes of algorithms: (i) "texture synthesis" algorithms for generating large image regions from sample textures (ii) "inpainting" techniques for filling in small image gaps. The former has been demonstrated for "textures" repeating two-dimensional patterns with some stochasticity; the latter focus on linear "structures" which can be thought of as one-dimensional patterns, such as lines and object contours. This project presents a novel and efficient algorithm that combines the advantages of these two approaches. We first note that exemplar-based texture synthesis contains the essential process required to replicate both texture and structure; the success of structure propagation, however, is highly dependent on the order in which the filling proceeds. We propose a best-first algorithm in which the confidence in the synthesized pixel values is propagated in a manner similar to the propagation of information in inpainting. The actual colour values are computed using exemplar-based synthesis. Here the simultaneous propagation of texture and structure information is achieved by a single, efficient algorithm. Computational efficiency is achieved by a block-based sampling process. A number of examples on real and synthetic images demonstrate the effectiveness of our algorithm in removing large occluding objects as well as thin scratches. Robustness with respect to the shape of the manually selected target region is also demonstrated. Our results compare favorably to those obtained by existing techniques. The "valid" pixels of the source region serve as examples for filling the Lacuna region. In computer vision, texture synthesis algorithms generate a large area of similar texture from sample texture or fill the lost region with input texture. Image inpainting algorithms are used to repair the scratches or cracks of photographs and paintings. Generally speaking, texture synthesis is applied to problems of single texture and image inpainting is used in general images with multiple textures.

The techniques are classified mainly into three categories. The first category is the synthesis of texture by simulating the physical generation process. The second category is the derivation of a parametric model by analyzing the input texture and synthesizing the output texture. However, these approaches are not able to capture the local features of texture. The third category of texture synthesis algorithms is the generation of the output texture by reproducing the sample texture. This is usually accomplished by synthesizing the pixels with the highest level of similarity to the Lacuna region. Texture synthesis has a variety of applications in computer vision, graphics, and image processing. An important motivation for texture synthesis comes from texture mapping. Texture images usually come from scanned photographs, and the available photographs may be too small to cover the entire object surface.

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7.Title: Image inpainting with salient structure completion and texture propagation.

Image inpainting technique uses structural and textural information to repair or fill missing regions of a picture. Inspired by human visual characteristics, we introduce a new image inpainting approach which includes salient structure completion and texture propagation. In the salient structure completion step, incomplete salient structures are detected using wavelet transform, and completion order is determined through color texture and curvature features around the incomplete salient structures. Afterwards, curve fitting and extension are used to complete the incomplete salient structures. In the texture propagation step, the proposed approach first synthesizes texture information of completed salient structures. Then, the texture information is propagated into the remaining missing regions. A number of examples on real and synthetic images demonstrate the effectiveness of our algorithm in removing occluding objects. Our results compare favorably to those obtained by existing greedy inpainting techniques.

. Image inpainting is an important topic in image processing, which can be applied in many areas, such as computer graphics, image editing, film postproduction, image res toration. Although image inpainting technique is very useful, the inpainting task is far from being a trivial accomplishment. It is still a challenging problem in computer graphics and computer vision. Image inpainting has attracted a considerable amount of re searches in recent years. Roughly speaking, existing image inpaint ing approaches can be divided into three categories. The first category is partial differential equation (PDE) based method intro duced by Bertalmio et al. (2000) and Chan and Shen (2001, 2002). These methods attempt to fill the missing regions of an image through a diffusion process which smoothly propagates informa tion from boundary toward interior of the missing region. This dif fusion process is simulated through solving a high order PDE. Bertalmio's method fills a hole in an image by propagating image information in the isophotes direction. Chan and Shen propose the total variational (TV) inpainting model inspired by Bertalmio's work. The TV inpainting model applies an Euler–Lagrange equation inside the inpainting region, and with simply employs anisotropic diffusion based on the contrast of the isophotes (Chan and Shen, 2001). The curvature-driven diffusion (CDD) model (Chan and Shen, 2002) extends the TV algorithm by considering geometric information of isophotes when defining the ''strength'' of the diffu sion process, thus allowing the CDD method to proceed over larger areas.

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8.Title: Free-Form Image Inpainting with Gated Convolution.

We present a generative image inpainting system to com plete images with free-form mask and guidance. The sys tem is based on gated convolutions learned from millions of images without additional labelling efforts. The proposed gated convolution solves the issue of vanilla convolution that treats all input pixels as valid ones, generalizes partial convolution by providing a learnable dynamic feature se lection mechanism for each channel at each spatial location across all layers. Moreover, as free-form masks may appear anywhere in images with any shape, global and local GANs designed for a single rectangular mask are not applicable. Thus, we also present a patch-based GAN loss, named SN PatchGAN, by applying spectral-normalized discriminator on dense image patches. SN-PatchGAN is simple in for mulation, fast and stable in training. Results on automatic image inpainting and user-guided extension demonstrate that our system generates higher-quality and more flexi ble results than previous methods. Our system helps user quickly remove distracting objects, modify image layouts, clear watermarks and edit faces. Image inpainting (a.k.a. image completion or image hole-filling) is a task of synthesizing alternative contents in missing regions such that the modification is visually realis tic and semantically correct. It allows to remove distracting objects or retouch undesired regions in photos. It can also be extended to tasks including image/video un-cropping, ro tation, stitching, re-targeting, re-composition, compression, super-resolution, harmonization and many others. In computer vision, two broad approaches to image in painting exist: patch matching using low-level image fea tures and feed-forward generative models with deep convo lutional networks. The former approach [3, 8, 9] can syn thesize plausible stationary textures, but usually makes crit ical failures in non-stationary cases like complicated scenes, faces and objects. The latter approach [15, 49, 45, 46, 38, 37, 48, 26, 52, 33, 35, 19] can exploit semantics learned from large scale datasets to synthesize contents in non stationary images in an end-to-end fashion. wever, deep generative models based on vanilla convolutions are naturally ill-fitted for image hole-filling be cause the spatially shared convolutional filters treat all input pixels or features as same valid ones. For hole filling, the input to each layer are composed of valid pix els/features outside holes and invalid ones in masked regions.

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9.Title: Evaluation of Image Inpainting Algorithms.

Image inpainting is a technique to repair damaged images or to remove/replace selected regions. It was used to repair old artwork and also a part of movie special effects. This paper presents review of many successful algorithms for image inpainting which are Texture based algorithms, Diffusion(PDE) based algorithms, Exemplar and search based algorithms and Sparsity based algorithms. Here an evaluation of two classes of algorithms: Partial Differential Equations (PDEs) based algorithms and Exemplar-Based algorithms are presented. The results show the advantages and disadvantages. Image inpainting is the technique of filling in the missing regions of an image using information from surrounding areas. In image inpainting, the missing region is often referred to as hole, and is usually provided by the user in the form of mask or can be obtained by automatic or semi-automatic means. Some of the earlier nomenclature referred small region filling as inpainting and large area inpainting as image or video completion. In this work however, we do not make any such distinctions and these techniques are commonly referred as Digital Image and video inpainting algorithms. Digital inpainting has found widespread use in many applications such as removal of undesired objects and writings on photographs, restoration of damaged old paintings and photographs, transmission error recovery in images and videos, computer-assisted multimedia editing and replacing large regions in an image or video for privacy protection. The inpainting means a technique is to modify the damaged portion or region in an image or video. Then the inpainted region is undetectable to a neutral observer is described in [1]. The objective of image inpainting is to reconstitute the damaged portions or regions of the imge, then that image is more legible and restore its unity. Based on the context of operation, the goal of the inpainting can range from making the damaged image or video appear as close to the original to completely providing an alternate completion which is virtually unnoticeable to human observer Image inpainting is an ill-posed inverse problem that has no well-defined unique solution. To solve the problem, it is therefore necessary to introduce image priors. All methods are guided by the assumption that pixels in the known and unknown parts of the image share the same statistical properties or geometrical structures. The first category of methods, known as diffusion-based inpainting, introduces smoothness priors via parametric models or partial differential equations (PDEs) to propagate (or diffuse) local structures from the exterior to the interior of the hole. Many variants exist using different models (linear, nonlinear, isotropic, or anisotropic) to favor the propagation in particular directions or to take into account the curvature of the structure present in a local neighborhood. These methods are naturally well suited for completing straight lines, curves, and for inpainting small regions. These are not well suited for recovering the texture of large areas, which they tend to blur.

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10.Title: Review on Recent Patents in Texture Synthesis.

Computer graphics applications often use textures to render synthetic images. These textures can be obtained from a variety of sources such as hand-drawn pictures or scanned photographs. Texture synthesis is an alternative way to create textures. Because synthetic textures can be made any size, visual repetition is avoided. The goal of texture synthesis can be stated as follows: given a texture example, synthesize a new texture that, when perceived by a human observer, appears to be generated by the same underlying process. This paper reviews the recent patents on texture synthesis schemes. The key components in a texture synthesis algorithm, such as neighborhood matching, block sampling, anisometric synthesis, etc., are discussed. Then we discuss the applications of texture synthesis in texture magnification and image repairing. This paper also points out future works on this issue. Reproducing detailed surface appearance is important to achieve visual realism in computer rendered images. One way to model surface details is to use polygons or other geometric primitives. However, as details becomes finer and more complicated, explicit modeling with geometric primitives becomes less practical. An alternative is to map an image, either synthetic or digitized, onto the object sur face, a technique called texture mapping. The mapped im age, usually rectangular, is called a texture map or texture. A texture can be used to modulate various surface proper ties, including color, reflection, transparency, or displace ments. In computer graphics the content of a texture can be very general; in mapping a color texture, for example, the texture can be an image containing arbitrary drawings or patterns. Generating novel photo-realistic imagery from smaller examples has been widely recognized as a significant problem in computer graphics. A wide number of applica tions require realistic textures to be synthesized for object decoration in virtual scenes. Texture refers to the class of imagery which is usually defined as an infinite pattern consisting of stochastically stationary repeating elements. The global repeatability within texture images is essential to texture synthesis techniques. This inherent property also makes it possible to express adequate texture infor mation with limited portions. Texture synthesis is an efficient way to create textures because synthetic textures can be made any size, visual repetition is avoided. Texture synthesis can also produce tileable images by properly handling the boundary condi tions. The objective of texture synthesis can be stated as follows. Given an example texture (Figure 1), synthesize a new texture that, when perceived by a human observer, appears to be generated by the same underlying process (Figure 1(b)). In this paper, we will first discuss the various example based texture synthesis algorithms. Then we review the recent authorized patents in this area and the texture synthesis-based applications such as style transfer, texture magnification and image repairing.

References:

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