1. INTRODUCTION
Image inpainting [1,2] provides a means to restore damaged region of an image, such that the image looks complete and natural after the inpainting process. Inpainting refers to the restoration of cracks and other defects in works of art. A wide variety of materials and techniques are used for inpainting. Digital inpainting are used to restore old photographs to their original condition. Recently we are using digital imaging with different techniques and approaches. The purpose of image inpainting is to remove damaged portions of an aged photo, by completing the area with surrounding or global information. The techniques used include the analysis and usage of pixel properties in spatial and frequency domains. Furthermore, image inpainting techniques are used in object removal (or image completion) in photos.

2. INPAINTING
Aged films may contain defects such as spikes or dirt, as well as long vertical defect lines. These defects may be produced in file development or due to improper maintenance of films. We present an algorithm, which can detect and restore defects. In addition, the restoration technique is used with a motion tracking mechanism. Objects can be removed and holes can be inpainted.

In inpainting we will be able to detect and remove thin artifacts, characters printed on pictures. First, the user provides the inpainting area or uses an image crack detector. With the known area, the inpainting will fill the gap using sophisticated techniques including:

- Transportation used to move pixels from outside to inside cracks, taking account the details of the neighbor pixels.
- Diffusion propagates your pixels from cracks borders, like something hot (the image) moves into a cold area (the crack area).
- Multiresolution Looking to smaller images first will ease the inpainting. The results are propagated to larger scales images.

This paper presents an inpainting algorithm, which implements the filling of damaged region with impressive results. Many algorithms usually require several minutes on current personal computers for the inpainting of relatively small areas. Such a time is unacceptable for interactive sessions and motivated us to design a simpler and faster algorithm capable of producing similar results in just a few seconds. The results produced by the algorithm are two to three orders of magnitude faster to the existing. The effectiveness of our approach is illustrated with examples of restoration of photographs, vandalized images, and text removal.

Keywords: Inpainting, Digital Inpainting Techniques, Tornado, Exemplar

ABSTRACT
This paper presents an inpainting algorithm, which implements the filling of damaged region with impressive results. Many algorithms usually require several minutes on current personal computers for the inpainting of relatively small areas. Such a time is unacceptable for interactive sessions and motivated us to design a simpler and faster algorithm capable of producing similar results in just a few seconds. The results produced by the algorithm are two to three orders of magnitude faster to the existing. The effectiveness of our approach is illustrated with examples of restoration of photographs, vandalized images, and text removal.

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Fig. 1.0

RAW Image Processing

Traditional Digital Inpainting Techniques
Whether we are using Adobe Photoshop, Fireworks or another image-editing program, different inpainting techniques can be applied, depending on what we are attempting to correct. The most common subject of corrections is photographs. Some of the most frequent issues are cracks across the image from prior folding, tearing at the edges or date stamps imprinted on the surface. One method of correcting such eyesores is to use a diffusion-based inpainting macro (add-on) developed for use within Photoshop. Another effective method is what is known in Adobe Photoshop as the Clone Stamp tool and in Adobe Fireworks as the Rubber...
Digital inpainting is an algorithm that uses one-pixel thick boundaries and reconnects edges reaching &! by clearing its color information and merging the regions to be inpainted. With a fast TV Inpainting supporting isotropic diffusion process that propagates information from &! to high contrast edges. Thus, let &! be a small area to be inpainted and &! be its boundary. Since &! is small, the inpainting procedure can be approximated by an isotropic diffusion process that propagates information from &! into &!. A slightly improved algorithm reconnects edges reaching &! by clearing its color information and repeatedly convolving the region to be inpainted with a diffusion kernel. &! is a one-pixel thick boundary and is used in inpainting / image completion, video inpainting and 3-D surface completion. The purpose of image inpainting was to remove damages portions of an aged photo, by completing the area with surrounding or global information. The techniques used include the analysis and usage of pixel properties in spatial and frequency domains[4]. Furthermore, image inpainting techniques were used in object removal (or image completion) in photos. Several strategic algorithms were developed based on confidence values and priorities of using patches. The techniques used in still images were then extended to video inpainting[7], which need to consider temporal properties[3] such as motion vectors. With a reasonable combination of object tracking and image completion, objects in video can be removed and possibly replaced. On the other hand, aged films contain two types of defects: spikes and lone vertical lines. These defects need to be precisely detected and removed to restore the original film. In addition, based on image completion techniques, incompleteness of scanning results of a 3-D scanner due to improper location or other reasons of a scanner can be solved. It covers image inpainting, video inpainting[7], 3-D surface inpainting.

**Exemplar Based Method[8]**: Exemplar based methods are becoming increasingly popular for problems such as denoising, super resolution, texture synthesis, and inpainting. The common theme of these methods is the use of a set of actual image blocks, extracted either from the image being restored, or from a separate training set of representative images, as an image model. In the case of inpainting, the approach is usually to progressively replace missing regions with the best matching parts of the same image, carefully choosing the order in which the missing region is filled to minimize artifacts. We can go for an inpainting method that represents missing regions as sparse linear combinations of other regions in the same image (in contrast to, in which sparse representations on standard dictionaries, such as wavelets, are employed), computed by minimizing a simple functional.

**Inpainting Algorithm**: Images may contain textures with arbitrary spatial discontinuities, but the sampling theorem constraints the spatial frequency content that can be automatically restored. Thus, for the case of missing or damaged areas, one can only hope to produce a plausible rather than an exact reconstruction. Therefore, in order for an inpainting model to be reasonably successful for a large class of images the regions to be inpainted must be locally small. As the regions become smaller, simpler models can be used to locally approximate the results produced by more sophisticated ones. Another important observation used in the design of our algorithm is that the human visual system can tolerate some amount of blurring in areas not associated to high contrast edges. Thus, let &! be a small area to be inpainted and let &! be its boundary. Since &! is small, the inpainting procedure can be approximated by an isotropic diffusion process that propagates information from &! into &!. A slightly improved algorithm reconnects edges reaching &! by clearing its color information and repeatedly convolving the region to be inpainted with a diffusion kernel. &! is a one-pixel thick boundary and
the number of iterations is independently controlled for each inpainting domain by checking if none of the pixels belonging to the domain had their values changed by more than a certain threshold during the previous iteration. Alternatively, the user can specify the number of iterations. As the diffusion process is iterated, the inpainting progresses from $\partial \Omega$ into $\Omega$. Convolving an image with a Gaussian kernel (i.e., computing weighted averages of pixels’ neighborhoods) is equivalent to isotropic diffusion (linear heat equation). Our algorithm uses a weighted average kernel that only considers contributions from the neighbor pixels (i.e., it has a zero weight at the center of the kernel). Figure 2 shows the pseudo code of the algorithm and two diffusion kernels. All reconstructed images shown in this paper were obtained with this algorithm or with a minor variation of it.

**SIMULATIONS AND RESULTS**

![Figure 2: a) Original Photo, b) Mask Image, c) the Final Result](image)

**Inpainting a 12-Mpixel Photograph**

![Figure 3. a: An Image with Characters](image)  
![Figure 3. b: The Image Removed the Characters](image)  

![Figure 4. a: An Image with Characters](image)  
![Figure 4. b: The Image Removed the Characters](image)  

![Figure 5. a: Original Photo, b) Mask Image, c) The Final Result](image)
3. CONCLUSION

We use three tools for spike detection and restoration, long vertical line detection and repairing, and object removal and inpainting. Results of restored video[3] clips show that our mechanisms are practical with good inpainted video quality. The implementation of the proposed inpainting methods exhibits high computational cost, but delivers better results than the significantly more conceptually complex methods with which it is compared, providing evidence of the potential of the proposed approach. A number of significant improvements remain to be considered, including application of a more appropriate solver for the minimization problem.

REFERENCE


