Review of Image Inpainting

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Abstract. This paper focuses on the mainstream three image restoration method, which is based on image restoration technology, based on a priori smoothness of image inpainting, texture similarity based on a priori statistical prior of image inpainting technology, according to the most popular method for the image inpainting. This paper introduces the advantages and disadvantages of them.

Introduction

Digital image restoration cannot restore the original content of the missing information accurately, and usually more focus on the pursuit of the restoration knot.The overall and local rationality of the fruit, as well as no perceptible trace of the human eye, makes the result of the restoration conform to the people's concern.The cognitive psychology of things. Gestalt cognitive psychology holds that [1] is a global perception of multiple parts in a regular form, rather than a simple set of individual perception. Corresponding to human. For the understanding of the image, the human perception of the integrity of an image is based on the content of the image. Human cognition is based on the cognition of the things, features and organizational arrangements in the image. In a nutshell, one Images that conform to human visual integrity should meet the following three rules: in the part of the image, a pixel and a pixel. The surrounding pixels are basically uniform in color and brightness values, structural content in the image, such as lines,
Contours, etc., are continuous and consistent on the whole; image areas belonging to the same kind of content, in color and grain.

The characteristics of the principle are similar. Therefore, for the digital image restoration technology, it is only in the design of human to take into full consideration. The basic cognitive laws of the image can produce high quality and satisfactory restoration results, and this is the current digital map. The basic starting point and final purpose of the repair technology.

Image restoration can be expressed in mathematics as an ill posed inverse problem (ill-posed inverse problem). Theoretically, there is no unique solution. Therefore, it is necessary to introduce appropriate prior assumptions to solve this problem. When proposing a local or global prior model, it is usually assumed that the pixels of known and unknown parts of the image are the same and coherent in statistical attributes and geometric structures, and such a hypothesis is actually consistent with human cognition of things mentioned above. A priori knowledge of image using the current digital image restoration in the field is divided into three categories: the smoothness constraint, constraint prior image texture content for image smoothing as texture similarity prior and the construction of statistical prior based on the global image of the main structure. The image restoration technologies constructed by these three kinds of priors are [4]: image smoothing technology based on smoothness priori, image inpainting technology based on texture similarity prior, and image inpainting technology based on statistical prior model. This chapter will give a general introduction to the main algorithms of these three types of technology.

Image Restoration Technology based on Smoothness Prior

A smoothness priori holds that every pixel in the image is only related to its neighboring pixels, and it is uniform and smooth, and there is no jump of pixel value. Otherwise, it will produce visual effects similar to noise. There are two ways to realize the smoothness prior: Based on partial differential

equations and based on variation. The standard partial differential equation based method usually has a large amount of computation and the content of image edge contour can not be well preserved. In order to solve such problems, there are many kinds of image inpainting technology based on anisotropic diffusion. Telea et al. [3] proposed a method of fast estimation of unknown pixels by weighted averaging of calculated pixel values. Tschumperle et al [4] proposed a tensor driven partial differential equation model is regularized multi value image, such as RGB color image and multispectral image, video and so on, through the use of heat to constrain the integral curve in the calculation to better preserve the image structure of the curvature in the repair results. Compared with the direct diffusion method, the advantage of variational based method is the preservation of local marginal content of image, and the drawback is the connectivity of image local lines. In order to solve this problem, Chan et al [5] proposed the curvature driven diffusion model and Shen et al [6] proposed based on Euler elastic function model based on the core idea of the energy function are another consideration the regularization edge structure is introduced.
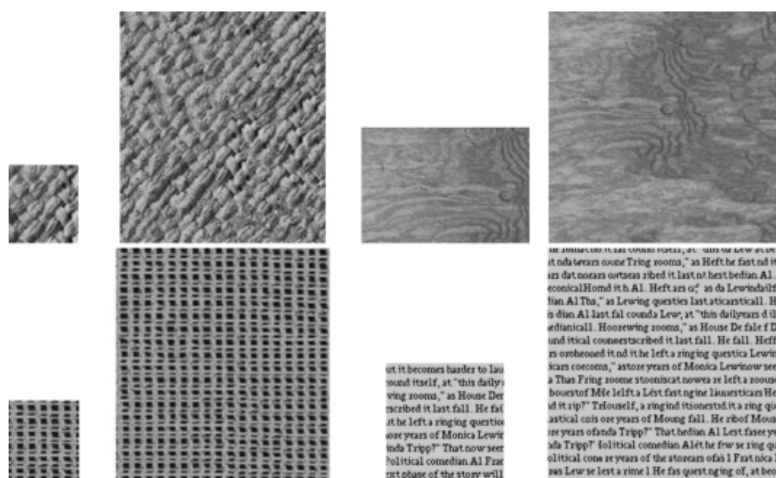

Figure 1. Texture synthesis example, building large size textures based on each small size sample texture

Image Restoration Technology based on Texture Similarity Priori

Pixel based image inpainting technology is mainly achieved through the establishment of Markov random field (Markov Random Fields, MRFs), but it is different from the standard Markov random field method using probability graph model. Texture synthesis algorithm proposed in the paper [7][8] have adopted a similar operation, the target image of each pixel as the center of the image block, looking for a certain distance in the scales of most similar image blocks in the global image, and the matching to the center pixel image block is copied to this before the pixel to be filled in. This way ensures the coherence of every filled value with the surrounding pixels, and because each pixel value comes from the image content itself, so that the overall visual consistency of the image is ensured, which is consistent with human cognitive psychology. The texture synthesis technology is applied to image restoration followed the same idea: for the image damage every pixel in the area according to the texture synthesis from the global search for the nearest neighbor, the nearest neighbor search way based on neighborhood image block matching, will be copied to the nearest neighbor pixels to fill damaged pixels the whole process, in accordance with the filling gradually from the edge to the damaged area inside the damaged area of. The essence of pixel by pixel filling method is greedy, which often leads to a completely repetitive structure in the repair result, which makes the image as a whole is consistent, but it doesn't seem natural. In order to solve these problems, a restoration technology based on image block exemplar is developed, that is, the process of repair is to copy every block of a whole image to the damaged area by sampling each time [9][10][11][12][13].
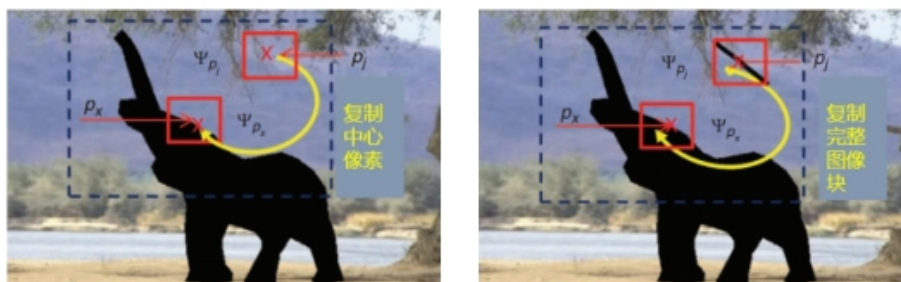
Figure 2. Comparison of image restoration techniques based on sample examples based on pixels

Image Repair Technology based on Statistical Prior

The statistical priori of images refers to some rules that are usually followed by the observation and statistics of a large number of image contents. These rules can be used to guide some image processing problems, including image denoising, image inpainting, super resolution and so on. In image inpainting, the known information is only part of the observed value in the image, and for every unknown pixel, it can exist at any value without other constraints, which leads to the ill posed inverse problem with infinite solutions. But the key point of an image from a random number matrix is that for any type of image, whether it is art or photography, image content transfer of human can accept and understand the information, generally consistent with human perception of things, and this is consistent with human cognitive psychology the information usually meet some specific properties in statistics. Therefore, when repairing a damaged image, it is reasonable to assume that the restoration result should satisfy some specific image attribute, so that we can solve the optimal solution that accords with human cognition under this constraint condition. The model used here to describe the characteristics of the statistical image is called a statistical prior model of the image. According to the method and emphasis of the image statistics rule of different content, usually have multiple description of different prior image attributes, such as focusing on [14], some distribution characteristics in image brightness value of some [15], focuses on the distribution characteristics of the gradient image from some image transform [16], statistical law domain directly or through some methods machine learning for image content of statistical learning and modeling [17].

Figure 3. Example of low rank texture repair

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