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An Overview of Restoration Algorithms for Digital Images

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Abstract: Image restoration refers to the process of restoration of lost or corrupted data in the image. In recent years, numerous methods with different functions in the reconstruction of noisy images or text replacement, hiding waste in the context of transferring of corrupted image, object removal in the context of editing, or removing the image prohibition on the transfer of image-based perspectives are presented which are distinct from the photos taken by the cameras. This article attempts to investigate the most appropriate and satisfactory method among different algorithms of image restoration. Scattered frequencies are considered to remove restoration problem with the emergence of sporadic cases and intensive observations. Scattering-based techniques are more suitable for filling large context areas. The algorithm is based on the assumption that the image (or patch) on a specified basis, spread (i.e., discrete cosine transform (DCT) or shock waves) with the goal that the restored image to be physically acceptable and satisfactory in appearance.

Keywords: Image Restoration, Object Removal, Scattering-Based Restoration

1. Introduction

The term "restoration" long before has been used by museum restoration artists. For example, in the reconstruction of ancient paintings or old pictures, a part of the image or frame has been lost part or has been damaged due to graze, hit, etc. In recent years, great progress has been made in the field of restoration that has been highly modified by applications such as the reconstruction of noisy images or text replacement, hiding waste in the context of the transferring the corrupted file, object removal in the context of editing, or removing the image prohibition in the transmission of image-based views (IBR), which are distinct from images taken from cameras [1]. The initial effect which removes the image prohibition has been published in [2].

Unlike problems that have multiple solutions, a specified and systematic solution has not been found for image restoration. Therefore, it is necessary to present previous works of the images to fix the problem. In this overview study, it is assumed that specified and unspecified sectors of the image have same scattered sample.

Previous methods, including Diffusion-Based algorithms (Diffusion-Based In painting) require repeated numerical methods (isotopic, non-isotopic) and are relatively slow [1]. In the restoration of flat piece images, straight lines, curves, filling small spaces are suitable. They are not good for uneven images, especially if the area to be filled is large (Figure 1).

__Figure 1.__ The effects of stain removal, approach based on the diffusion (a) and (b), which the filling cavity is large and it is associated with spots and blur.

Sample-based methods [1] have a tremendous impact on the context areas with homogeneous and regular patterns. The aim is to create a context from specified samples in such a way that it is larger production context than origin sample with same appearance. However, they are not suitable for retaining the edges or structures or images with very small distributed holes (Figure 2).

Damaged area can be selected in different ways. The oldest methods used a human expert to do so. These methods are concise but time-consuming. Other methods inspect a threshold to differentiate the damaged area from other parts of the image. The benefit of these methods lies in their speed however they aren't precise. There are some recent works to automatically find the damaged area with promising accuracies like the study done by Zhang et al. [8].

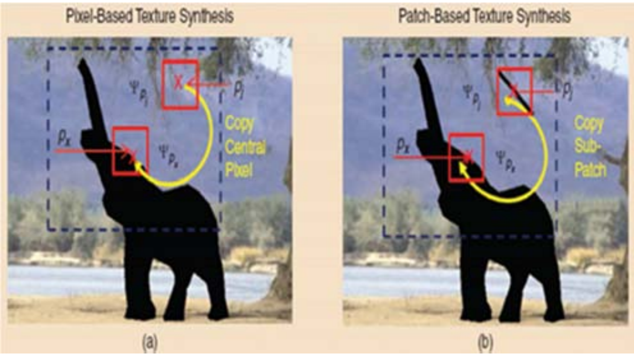

Figure 2. *Principles of sample-based methods: Searching for the patch that is most similar to the specified area and completing input patch and the central pixel (a) pixel-based approaches or (b) a set of pixels for patch-based approaches.*

2. Dispersion-Based Algorithm

According to mathematical law, it is defined as follows:

$$I:\left|\begin{array}{l}\Omega \subset R^n \ \rightarrow R^m \\ \quad x \rightarrow I(x),\end{array}\right.$$

Where X indicates a vector which is the space peculiarity of pixel px which is defined as (n=2) like x= (x, y) in the case of two-dimensional image. In the case of color images, each pixel containing three color components (m=3) is defined in the (R, G, B) color space. Each color channel of cth image show I as Ic: Ω → R. In restoration problem, it is assumed that the input image I (each image color channel) investigates the reduced operator (which is shown with M) to remove the sample from the image. As a result, the Ω comprehensive definition area of the input image I can be seen that consists of two parts: Ω = SUU, S is the specified section of image I (the source) and U is the unknown section of image which we try to estimate. Reduced version of seen F can be expressed as F = MI. The aim of restoration is to estimate Px pixel color components located at x in the unknown section of U from pixels located in the known region S, so that finally create the restored image.

The restoration problem can be solved given the frequency distributions of the image. In this case, it is assumed that the image I, is a sign of the earth dispersion [3]. This means that the image I is in dispersion in specific terms. The base can be created by predefined primary wave forms (the atom), which are stored at the matrix A dictionary. A dictionary Matrix can be learned by using learning methods. It is said that the image I is dispersion K in particular base which are stored in the A dictionary matrix, if it is displayed with vector v which has nonzero K component (i.e. lo, ││v││o = k norm) that proves I = Av. dispersion has a sign of dependency to the desired basis, i.e. matrix A. Thus, according to the image F = MI, restoration problem because of searching dispersed display vector v, F image is formulated by solution:

$$\min ││v││o$$

So that

$$F=Mav \qquad (1)$$

Most of the solutions exist for searching dispersed vector v with common solutions depended on greedy algorithms of adaptive path. An overview of the adaptive path algorithms can be found in [3].

The above inverse problem is usually solved through a patch to patch solution rather than directly in picture F. For each patch Ψpx of image F through the Ψspx known section and ΨUpx unknown section, everyone who is in search of vpx dispersed vector that have the most similarity with known section of Ψspx input patch like Ψspx = Aspx which is taken as the AS matrix obtained from the coverage of rows of the matrix A which is pursuant to unknown pixels ΨUpx, in Ψp shown in Figure 3.

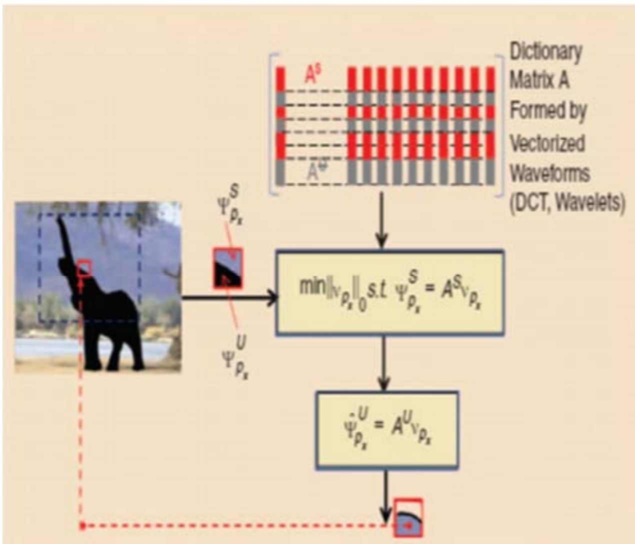

Figure 3. *The estimation of unknown pixels with dispersion frequencies in the transmission area. Dictionary matrix is composed of wave forms. The gray section of dictionary columns represent masked columns, which correspond to the position of unknown pixels in input patches.*

Dispersed linear combination of atoms are used for the similarity to the unknown pixels ΨUpx, like AUvp = ΨUpx, involve cover samples of atoms (the examples correspond to the status of unknown pixels). The general formula for other problems of image processing like removing scratches and high resolution is used. Dispersed display area is extended to the basis of more comprehensive sampling which is commonly used for image restoration problems.

Variables have been proposed using dispersion frequencies. It is assumed that the images are composed of areas with the same location which are separated by the edges. The author [4] uses the dispersion compatible shows. The nonlinear similarity algorithm is done with dispersion limitations which is consistently determined. Dispersed combining performances which confirm both local and nonlocal complexities are examined in [5]. Nonlocal dispersion as array dispersion of three-dimensional with input patches and K-NN [1] are formed in the known part of the image, while local dispersion is defined as two-dimensional patch dispersion. Dispersion limitations with hard threshold based on pre-defined waveform (DCT, Fourier fast transform) will be executed. Then local and nonlocal shows are combined through averaging base model [5] which estimates both ranges of local smoothness and nonlocal similarity with the restriction of known samples estimates accuracy.

Patch-based methods [1] show that context patches can be related to dictionary factors. Hence, instead of using pre-defined waveforms, linear combination of candidate patches which are set with the dispersion frequencies in the weight coefficients can be used for unknown pixels deduction. The dispersion is used to determine the structural patches that are processed first. In addition, dispersed display of the patch is limited with compatibility of local patch.

3. Combined Methods Which Separate the Structure from the Context

As mentioned previously, publishing methods for piece images are smooth and are suitable for the release of sturdy structures, but they are not able to repair the context. In contrast, sample-based methods have a tremendous impact on areas with homogeneous and regular patterns. They are not suitable to keep the edges or structures or images with very small distributed holes.

However, natural images include structures and complex contexts. The structures include image sketches (such as edges, corners) and context is areas with congruent patterns or statistical properties. Therefore, it is obvious that for using of textures and complex structures, different ways are combined. Two main strategies are evaluated. The first strategy involves the separation of image components (texture and structure) and restoring them separately with the best methods (such as diffusion or sample-based method), which, two same restoration components [6] are added. Ciotta and Androutsos presented a method to separate the image completion process into structure and texture synthesis. Their method used a morphological diffusion-based operation to construct the depth map of image. Then, the depth values are used to fill the missing color image texture [9].

The second strategy involves the combination of various techniques in a unique energy function that uses a variation formulation.

4. Texture/Structure Separation

Structures can be detected by monitoring method where the user specifies curves consistent with important lost structures (such as the range of the object) in an unknown area. Structure diffusion by copying patches located in the path of the curves is carried out in the known region. Unknown pixels remaining in the third stage are the estimate which uses texture composition procedure.

Texture and structure can be automatically separated. For example, a similar change method [6] can be used. The authors analyze the image as the sum of two functions, one function of bounded variation (BV), which represents the image structure, and the second one receives texture function. Structural image is the surface similarity of the input image containing only edges that only separate flat areas. The piecewise flat images refer to cartoon images in [6]. In [6], the texture layer is restored using texture composition [7], while the geometric layer is restored through diffusion and two important components are added together for a final conclusion.

Another method is proposed based on dispersion displays image analysis into texture and geometry component called layers. The image is divided into structural and textural components as I = Agvg + Atvt using two dictionaries with different specifications Ag and At. This method is called morphological component analysis (MCA). Two dictionaries are mutually contradictory, i.e. each dictionary provides dispersion display for a component, while the other provides non-dispersion for the other component. Both dictionaries are grouped to a large dictionary which is used through track-based algorithm to find the dispersion display of each layer. Therefore, an algorithm is proposed based on the dispersion which searches the image separation of two components. Instead of separate processing of two elements [6], scattering vectors for the two components are obtained with the decrease of:

$$\min \| vg \| p + \| vt \| p$$

that:

$$F = M(Agvg + Atvt)$$

Where $\| 0 \| p$ shows Lp norm which is often equal to zero or one. To solve this reduction problem, the so-called penalty range is proposed. The term penalty TV is added for regulating the dispersion approximation. This approach can be filled in the area with textures and complex structures. However, when the destroyed area was large introduces the darkness. Patch is limited with the local patch compatibility.

Neural networks can be used in image restoration too. Wang and Tao mention that conventional neural networks are unstable regarding their internal propagation [10]. They inspected self-similar information in natural images for stability. They believe that similar inputs should have similar network propagation. To reach this, they constrained the difference between the hidden representations of non-local similar image blocks during training.

5. Function

One of the normal functions of restoration is image editing in a place where the user deletes objects. Therefore, unknown parts reveal image background. This use has been shown in Figure 4 well in which a foreground object is deleted; it provides the possibility of filling the hole.

6. Discussion and Conclusion

In this paper, overview of digital photos' image restoration algorithms was presented. Dispersion-based algorithms compared to other previous algorithms are more suitable for modifying hole texture. In Table 1, the specifications, application usages and the comparison of various methods of image restoration has come together.

Since the quality assessment of restored images is a complex and unresolved problem (because there are no quantitative metrics), therefore we must rely on subjective evaluation to assess whether the restored images are visually satisfying and acceptable in terms of the appearance. It is hoped that we can develop these techniques in the future to make stronger algorithms in the direction of better quality of digital images restoration.

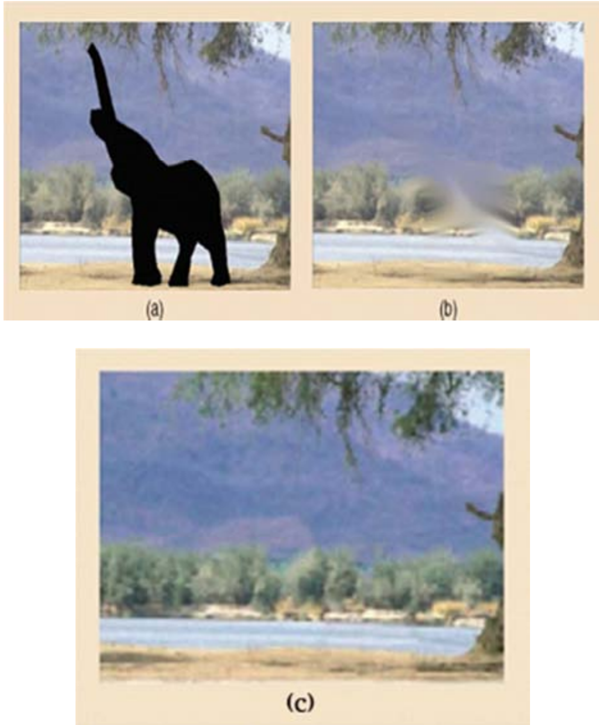

Figure 4. *The Application of the object removal. (a) mask and restoration results using various categorization methods, (b) the previous method (non-isotopic release), (c) patches dispersion display.*

Table 1. *Restoration methods classification.*

Specifications	Diffusion-based	Sample-based	Combined methods	Comprehensive methods
Frequency	Smoothing	Self-similarity, dispersion	Smoothing + similarity / dispersion	Statistical, lower class
Optimization	Greedy	Greedy or comprehensive	Greedy or comprehensive	comprehensive
Launching sensitivity	Low	High	High	High
Holes	Small	Medium to large	Medium to large	Small to medium
Application usages	Restoration	Restoration, editing, removing the prohibition of image, hiding	Restoration, editing, removing the prohibition of image, hiding	Restoration

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