Recovery of Image by Object & Noise Removal by Using Enhanced Inpainting Technique

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Abstract- Image inpainting is a technique of filling unknown image regions with known information from the surroundings of the unknown region in such a way that the result is logically accepted. Image inpainting has become a standard tool in image and video processing with many applications to image recovery. In this paper, a new method for noise reduction & removing a large object from digital images. Median filter is used to decrease the blurring problem. Proposed method designed for the recovery of small scratches, and in instances in which larger objects are removed.

Keywords- Noise removal, Median filtering, Image inpainting.

I. INTRODUCTION

Image inpainting, is an active area of research in image processing. It aims to obtain a visually probable interruption in the region of the image where the data is missing or we want to just modify it. It has become a standard tool in image and video processing with many applications to image restoration (e.g., scratch or text removal in photographs), new view synthesis (e.g., filling the dis-occluded regions), object removal, image coding and transmission (e.g., recovery of the missing blocks), etc. [1]. In the literature of digital image processing, many methods have been proposed over the years to solve the problem of image degradation due to impulsive noise [2]. Images are normally corrupted by impulse noise during acquisition or transmission resulting in the degradation of the image quality and the interpretability. In an image corrupted by the fixed-valued impulse noise, the amplitude of the corrupted pixels will be either the maximum or the minimum value of the dynamic range, whereas the amplitude of the corrupted pixels in an image corrupted by random-valued impulse noise is spread over the entire dynamic range. The problem of image inpainting is solved using sparse representations. It is shown that an image can be reconstructed even if 80% of its pixels are missing. This led to a revolution in the correction stage of the two-stage impulse denoising methods. Most of these methods detect the presence of impulses using some existing methods. The detected impulses are then considered to be holes and are reconstructed using sparse representations [3]. A texture synthesis as a way to fill large image regions with pure textures repetitive twodimensional textural patterns with moderate stochasticity. This is based on a large body of texture-synthesis research, which seeks to replicate texture ad infinitum, given a small source sample of clean texture. Of particular interest are exemplar-based techniques which cheaply and effectively generate new texture by sampling and copying color values from the source [4]. In general, the goal is to recover an unknown true image from a noisy measurement [5].

In this paper, a new method for noise reduction & removing large objects from digital images is proposed. Decision-Based Adaptive median filter (DBA) used in the proposed method to decrease the blurring problem. Proposed method designed for the recovery of small scratches, and in instances in which larger objects are removed.

II. BACKGROUND

Mainly inpainting methods found in the literature can be classified in two main categories: geometry- and exemplar-based methods. In geometry-based methods, images are usually modeled as functions with some degree of smoothness. They take advantage of the smoothness assumption and interpolate the inpainting domain by continuing the geometric structure of the image (its level lines, or its edges), usually as the solution of a (geometric) variational problem, or by means of a partial differential equation (PDE). These methods show good performance in propagating smooth level lines or gradients, but fail in the presence of texture. They are often referred to as structure inpainting methods. Exemplar-based methods based on texture synthesis using non-parametric sampling techniques. In this context, texture is modeled as a two-dimensional probabilistic graphical model, in which the gray or color value of each pixel is conditioned by its neighborhood. These methods rely directly on a sample of the
desired texture to perform the synthesis [1]. Median filters are among the most popular image filtering techniques used to eliminate noise. The main idea in standard median filtering (SMF) is to slide a square window of length \((2k + 1)\) over the entire image and replace the central pixel in the window by the median value of all the pixels in the same window. The effective noise suppression obtained using this method is accompanied by blurred and distorted features, thus loosing image fine details and edges [2]. Non-linear filtering techniques are proven to be effective to remove impulse noise from an image. The standard median filter is a simple nonlinear filter that replaces each pixel in the image by the median of the neighboring pixels. This leads to change in the pixel values that are not affected by impulse noise, resulting in the loss of fine details like the edge and texture information associated with the image. To overcome this disadvantage, twostage methods are employed. In the detection stage, the positions of the noise pixels are detected. In the correction stage, the detected noisy pixels are modified based on some correction algorithm. Some detection-based filters are the multi-state median filter, the signal-dependent rank-ordered mean (SDROM) filter, the adaptive center weighted median (ACWM) filter and a switching median filter [3]. Liu et al. [1] proposed a novel formulation of exemplar-based inpainting as a global energy optimization problem, written in terms of the offset map. The energy function combines a dataattachment term that ensures the continuity of reconstruction at the boundary of the inpainting domain with a smoothness term that ensures a visually coherent reconstruction inside the hole. This formulation is adapted to obtain a global minimum using the graph cuts algorithm. To reduce the computational complexity, author proposed an efficient multiscale graph cuts algorithm. To compensate the loss of information at low-resolution levels, author use a feature representation computed at the original image resolution. This permits alleviation of the ambiguity induced by comparing only color information when the image is represented at low resolution levels. Ramadan et al. [2] proposed a new method for impulse noise reduction and edge preservation in images. Images of different characteristics corrupted with a wide range of impulse noise densities using two impulse noise models are examined using the proposed method. In the detection stage of the method, two conditions have to be met to determine whether an image pixel is noisy or not. Two predetermined threshold values are involved in the computation of the second condition to differentiate between corrupted and uncorrupted pixels. Only pixels determined to be noisy in the detection stage are filtered in the next filtering stage where small size sliding windows are used to significantly reduce blurring effects in the output restored images. Saikrishna et al. [3] proposes a iterative method for the removal of random-valued impulse noise from the images using sparse representations. Each iteration has three stages. In the first stage, the positions of the possible noise pixels are detected using a sparse representation of the pixels in a window. In the next stage, the pixels that are detected as noisy pixels are treated as missing pixels and are filled using image inpainting through sparse representations. In the third stage, the pixels noticed as noise pixels in the first stage are tested based on the inpainted value to determine the correctness of the noise detection at the first stage. In the subsequent iterations, the output of the previous iteration is considered to be the input for the detection and removal of the impulse noise. P’erez et al. [4] proposed a novel and efficient algorithm that combines the advantages of these two approaches. First 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. Xie et al. [5] proposed an efficient algorithm for solving an abalanced regularization problem in the frame-based imagerestoration. The balanced regularization is usually formulated as a minimization problem, involving a data-fidelity term, and regularizer on sparsity of frame coefficients, and a penalty on distance of sparse frame coefficients to the range of the frame operator.

### III. EXISTING METHODOLOGIES

Image inpainting using multiscale graph Cuts: The inpainting problem is formulated using an exemplar-based approach as an energy optimization problem for the offset map. The energy function consists of a data attachment term that ensures the good continuation of the reconstructed image at the boundary of the inpainting domain and a term that favors spatial coherence in the image completion. The formulation is adapted to obtain a global optimum using graph cuts. To reduce the computational complexity, an efficient multiscale graph cuts algorithm is used. A multiscale graph cuts algorithm efficiently solve the energy minimization problem in which a feature vector representation is introduced to compare patches at low resolution, to compensate the information loss. This representation can significantly eliminate ambiguities and improve the accuracy of the offset map [1]. Impulse Noise Elimination and Edge Preservation in images: Images of different characteristics corrupted with a wide range of impulse noise densities using two impulse noise models i.e. Noise model 1 & Noise model 2. This method contains of two stages: detection and filtering. In the detection stage of
themethod, two conditions have to be met to determine whether an image pixel is noisy or not. Two predetermined threshold values are involved in the computation of the second condition to differentiate between corrupted and uncorrupted pixels. Only pixels determined to be noisy in the detection stage are filtered in the next filtering stage. The remaining pixels (uncorrupted ones) are kept unchanged, where small sizesliding windows are used to significantly reduce blurring effects in the output restored images [2]. A method for detection and removal of the random-valued impulse noisefiltering the sparse representations is used to remove the random-valued impulse noise in the images. Each iteration has three stages. In the first stage, the positions of the possible nosie pixels are identified using a sparse representation of the pixels in a window. In the next stage, the pixels that are detected as noisy pixels are treated as missing pixels and are filled using image inpainting through sparse demonstration. In the third stage, the pixels detected as noise pixels in the first stage are tested based on the inpainted value to determine the correctness of the noise detection at the first stage. In the subsequent iterations, the output of the previous iteration is considered to be the input for the detection and removal of the impulse noise [3]. Exemplar-based texture synthesis technique modulated by a unified scheme for defining the fill order of the target region. Pixels retain a confidence value, which together with image isophotes, influence their fill priority. The technique is capable of propagating both linear structure and two-dimensional texture into the target region. 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. Best-first algorithm in which the confidence in the synthesized pixel values is spread in a manner similar to the propagation of information in inpainting. The actual color values are calculated using exemplar-based synthesis. Computational efficiency is achieved by a block-based sampling process [4].

IV. ANALYSIS & DISCUSSIONS

The method of region filling and object removal by exemplar-based image inpainting by defining a patch priority order based on structure sparsity that can better distinguish between texture and structure and is more robust to the continuation of edges. It also uses a sparse linear combination of exemplars to infer patches in a framework of sparse representation, improving the consistency of the selected patches with their surroundings. Most of the exemplar-based approaches are greedy procedures where each target pixel is visited only once, and the results are very sensitive to the order in which pixels are processed. Fig. 1 shows the results of random-valued impulse noise removal from the Barbara image corrupted by random-valued impulse noise of density 50% using different denoising techniques.

Fig. 1. Performance of various methods on Barbara image (a) Original Image, (b) Image corrupted by 50% Random-valued impulse noise, (c) SDROM filter output, (d) ACWMF output.

Patch Size in the Data Term: The size of the patch \( \Psi \) in the data term helps to capture the local image characteristics around the boundary of the hole, and get a good continuation of the image structure and texture. The practical rule: Fix the size of the patch for images at lowest resolution and increases linearly the size when doubling the resolution in each dimension. In practice, the lowest resolution image size considers around 80 \( \times \) 80 for which it uses a patch size of 7 \( \times \) 7. As an example, when the image size is 1000 \( \times \) 1000, the patch size is 17 \( \times \) 17. Figure 2 illustrates how the choice of patch size affects the quality of the inpainting result.

Fig. 2: Influence of the patch size on the results. (a) Image with mask. (b) \( wp = 3 \). (c) \( wp = 5 \). (d) \( wp = 11 \). (e) Adaptive.

2) Number of Multi-Scale Levels: In this, set up the size of the image at lowest resolution. The number of levels of the multiscale algorithm is set using the rule: consider one level of resolution for images of size \( a \times b \) and then adds the additional level when doubling the resolution in every dimension.

3) Search Range: For computational efficiency, set a restricted search range around the hole, specifying it by a bound on the maximum offset.

V. PROPOSED METHODOLOGY

The figure 3 shows basic steps of proposed method which consists of noise removal approach to remove the noise in the image and image inpainting algorithm to recover the
damaged image and to fill the areas which are absent in original image in visually plausible way.

![Diagram](image)

**Fig. 3. Steps for proposed method**

**Noise Removal:**
Adaptive Median Filter (AMF) perform well at low noisedensities. But at high noise densities the window size has to be increased which may lead to blurring the image. In switchingmedian filter the judgment is based on a pre-defined thresholdvalue. The major drawback of this method is that defining robust decision is difficult. Also these filters will not take intoaccount the local features as a result of which details and edgessmay not be recovered satisfactorily, especially when the noiselevel is high. To overcome the above problem, Decision BasedAdaptive Median Filter (DBA) is used. In this, image is denoised by using a 3*3 window. If the processing pixel values 0 or 255 it is processed else it is left unchanged. At highnoise thickness the median value will be 0 or 255 which is noisy. In such case, neighboring pixel is utilized forreplacements.

**Image Inpainting:**
Steps for Region-filling:
1. Computing patch priorities:
Filling order is crucial to non-parametric texturesynthesis. Thus far, the default favorite has been the “onionpeel" method, where the objective region is formed from theoutside inward, in concentric layers. Algorithm performs thisjob through a best-first filling algorithm that depends entirelyon the priority values that are assigned to each patch on the fillfront. The priority computation is inclined toward thosepatches which are on the continuation of strong edges andwhich are surrounded by high-confidence pixels.
2. Propagating texture and structure information:
When all priorities on the fill front have been computed, the patch with highest priority is found. Then fill it with dataextracted from the source region. In conventional inpainting techniques, pixel-value information is spread via diffusion.
3. Updating confidence values:
After the patch has been filled with new pixel values, the confidence is updated in the area surrounded. This simple updatetime rule allows measuring the relative confidence of patches on the fill front, without image specific constraints. As filling proceeds, confidence values decay, indicating that lessure of the color values of pixels near the centre of the target region.

**VI. CONCLUSION & FUTURE WORK**

This paper proposed a method for detection and removal of the noise & algorithm for removing large objects from digital photographs. The outcome of object removal is an image in which the selected object has been replaced by a visually plausible background that mimics the appearance of the sourcerregion. Pixels maintain a confidence value, which collectivelywith image isophotes, influence their fill priority. When the search range is too small one does not capture enough similar patterns. Currently, investigating extensions for more accurate propagation of curved structures in still photographs and for object removal from images, which promise to impose an entirely new set of challenges.

**REFERENCES**


