Recovery of Image by Object & NoiseRemoval by Using Enhanced InpaintingTechnique

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Abstract- Image inpainting is a technique of filling unknown image region with known information from the surrounding of the unknown region in such a way that the result is logically accepted. Image inpainting has become a standard tool in image and videoprocessing with many applications to image recovery. In this paper, a new method for noise reduction & removing a large objectsfrom digital images. Median filter is used to decrease the blurring problem. Proposed method designed for the recovery of smallscratches, 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 imageprocessing. It aims to obtain a visually probable interruption ina region of the image where the data is missing or we want justto modify it. It has become a standard tool in image and videoprocessing 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, imagecoding and transmission (e.g., recovery of the missing blocks),etc. [1]. In the literature of digital image processing, manymethods have been proposed over the years to solve theproblem of image degradation due to impulsive noise [2].Images are normally corrupted by impulse noise duringacquisition or transmission resulting in the degradation of theimage quality and the interpretability. In an image corruptedby the fixed-valued impulse noise, the amplitude of thecorrupted pixels will be either the maximum or the minimumvalue of the dynamic range, whereas the amplitude of thecorrupted pixels in an image corrupted by random-valuedimpulse noise is spread over the entire dynamic range. Theproblem of image inpainting is solved using sparserepresentations. It is shown that an image can be reconstructedeven if 80% of its pixels are missing. This led to a revolutionin the correction stage of the two-stage impulse denoisingmethods. Most of these methods detect the presence ofimpulses using some existing methods. The detected impulsesare then considered to be holes and are reconstructed usingsparse representations [3]. A texture synthesis as a way to filllarge image regions with pure textures repetitive twodimensionaltextural patterns with moderate stochasticity. Thisis based on a large body of texture-synthesis research, whichseeks to replicate texture ad infinitum, given a small sourcesample of clean texture. Of particular interest are exemplarbasedtechniques which cheaply and effectively generate newtexture by sampling and copying color values from the source[4]. In general, the goal is to recover an unknown true imagefrom a noisy measurement [5].

In this paper, a new method for noise reduction & removinga large objects from digital images is proposed. DecisionBased Adaptive median filter (DBA) used in the proposedmethod to decrease the blurring problem. Proposed methoddesigned for the recovery of small scratches, and in instancesin which larger objects are removed.

II. BACKGROUND

Mainly inpainting methods found in the literature can beclassified in two main categories: geometry- and exemplarbased methods. In geometry-based methods, images areusually modeled as functions with some degree of smoothness.

They take advantage of the smoothness assumption andinterpolate the inpainting domain by continuing the geometricstructure of the image (its level lines, orits edges), usually asthe solution of a (geometric) variational problem, or by meansof a partial differential equation (PDE).These methods showgood performance in propagating smooth level lines orgradients, but fail in the presence of texture. They are oftenreferred to as structure inpainting methods. Exemplar-basedmethods based on texture synthesis using non-parametricsampling techniques. In this context, texture is modeled as atwo dimensional probabilistic graphical model, in which thegray, or color, value of each pixel is conditioned by itsneighborhood. 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 toeliminate noise. The main idea in standard median filtering(SMF) is to slide a square window of length (2k + 1) over theentire image and replace the central pixel in the window by the
median value of all the pixels in the same window. Theeffective noise suppression obtained using this method isaccompanied by blurred and distorted features, thus loosingimage fine details and edges [2]. Non-linear filteringtechniques are proven to be effective to remove impulse noisefrom an image. The standard median filter is a simple nonlinearfilter that replaces each pixel in the image by the medianof the neighboring pixels. This leads to change in the pixelvalues that are not affected by impulse noise, resulting in theloss of fine details like the edge and texture informationassociated with the image. To overcome this disadvantage, twostage methods are employed. In the detection stage, thepositions of the noise pixels are detected. In the correctionstage, the detected noisy pixels are modified based on somecorrection algorithm. Some detection-based filters are themulti-state median filter, the signal-dependent rank-orderedmean (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-basedinpainting as a global energy optimization problem, written interms of the offset map. The energy function combines a dataattachment term that ensures the continuity of reconstruction atthe boundary of the inpainting domain with a smoothness termthat ensures a visually coherent reconstruction inside the hole.This formulation is adapted to obtain a global minimum usingthe graph cuts algorithm. To reduce the computationalcomplexity, author proposed an efficient multiscale graph cutsalgorithm. To compensate the loss of information at lowresolution levels, author use a feature representation computed
at the original image resolution. This permits alleviation of theambiguity induced by comparing only color information whenthe image is represented at low resolution levels. Ramadan etal. [2] proposed a new method for impulsive noise reductionand edge preservation in images. Images of differentcharacteristics corrupted with a wide range of impulsive noisedensities using two impulsive noise models are examined usingthe proposed method. In the detection stage of the metho, twoconditions have to be met to determine whether an image pixelis noisy or not. Two predetermined threshold values areinvolved in the computation of the second condition todifferentiate between corrupted and uncorrupted pixels. Onlypixels determined to be noisy in the detection stage are filteredin the next filtering stage where small size sliding windows areused to significantly reduce blurring effects in the outputrestored images. Saikrishna et.al [3] proposes a iterativemethod for the removal of random-valued impulse noise fromthe images using sparse representations. Each iteration hasthree stages. In the first stage, the positions of the possiblenoise pixels are detected using a sparse representation of thepixels in a window. In the next stage, the pixels that aredetected as noisy pixels are treated as missing pixels and arefilled using image inpainting through sparse representations. Inthe third stage, the pixels noticed as noise pixels in the firststage are tested based on the inpainted value to determine thecorrectness of the noise detection at the first stage. In thesubsequent iterations, the output of the previous iteration isconsidered to be the input for the detection and removal of theimpulse noise. P´erez et al. [4] proposed a novel and efficientalgorithm that combines the advantages of these twoapproaches. First exemplar-based texture synthesis containsthe essential process required to replicate both texture andstructure; the success of structure propagation, however, ishighly dependent on the order in which the filling proceeds.Xie et al. [5] proposed an efficient algorithm for solving abalanced regularization problem in the frame-based imagerestoration. The balanced regularization is usually formulatedas a minimization problem, involving a data-fidelity term, andregularizer on sparsity of frame coefficients, and a penalty ondistance of sparse frame coefficients to the range of the frameoperator.

III. EXISTING METHODOLOGIES

Image inpainting using multiscale graph Cuts: Theinpainting problem is formulated using an exemplar basedapproach as an energy optimization problem for the offsetmap. The energy function consists of a data attachment termthat ensures the good continuation of the reconstructed imageat the boundary of the inpainting domain and a term that favorsspatial coherence in the image completion. The formulation isadapted to obtain a global optimum using graph cuts. Toreduce the computational complexity, an efficient multiscalegraph cuts algorithm is used. A multiscale graph cutsalgorithm efficiently solve the energy minimization problem inwhich a feature vector representation is introduced to comparepatches at low resolution, to compensate the information loss.This representation can significantly eliminate ambiguities andimprove the accuracy of the offset map [1]. Impulse NoiseElimination and Edge Preservation in images: Images ofdifferent characteristics corrupted with a wide range ofimpulsive noise densities using two impulsive noise models i.e.Noise model 1 & Noise model 2. This method contains of twostages: detection and filtering. In the detection stage of themethod, two conditions have to be met to determine whetheran image pixel is noisy or not. Two predetermined thresholdvalues are involved in the computation of the second conditionto differentiate between corrupted and uncorrupted pixels.Only pixels determined to be noisy in the detection stage arefiltered in the next filtering stage. The remaining pixels(uncorrupted ones) are kept unchanged, where small sizesliding windows are used to significantly reduce blurringeffects in the output restored images [2]. A method fordetection and removal of the random-valued impulse noiseusing the sparse representations is used to remove the randomvalued impulse noise in the images. Each iteration has threestages. In the first stage, the positions of the possible noisepixels are identified using a sparse representation of the pixelsin a window. In the next stage, the pixels that are detected asnoisy pixels are treated as missing pixels and are filled usingimage inpainting through sparse demonstration. In the thirdstage, the pixels detected as noise pixels in the first stage aretested based on the inpainted value to determine thecorrectness of the noise detection at the first stage. In thesubsequent iterations, the output of the previous iteration isconsidered to be the input for the detection and removal of theimpulse noise [3]. Exemplar-based texture synthesis technique modulated by a unified scheme for defining the fill order of thetarget region. Pixels retain a confidence value, which togetherwith image isophotes, influence their fill priority. Thetechnique is capable of propagating both linear structure andtwo-dimensional texture into the target region. Exemplarbasedtexture synthesis contains the essential process requiredto replicate both texture and structure; the success of structurepropagation, however, is highly dependent on the order inwhich the filling proceeds. Best-first algorithm in which theconfidence in the synthesized pixel values is spread in amanner similar to the propagation of information in inpainting.The actual color values are calculated using exemplar-basedsynthesis. Computational efficiency is achieved by a blockbased sampling process [4].

IV. ANALYSIS & DISCUSSIONS

The method of region filling and object removal by exemplar-basedimage inpainting by defining a patch priority orderbased on structure sparsity that can better distinguish betweentexture and structure and is more robust to the continuation ofedges. It also uses a sparse linear combination of exemplars toinfer patches in a framework of sparse representation,improving the consistency of the selected patches with theirsurroundings. Most of the exemplar-based approaches aregreedy procedures where each target pixel is visited only once,and the results are very sensitive to the order in which pixelsare processed. Fig. 1 shows the results of random-valuedimpulse noise removal from the Barbara image corrupted byrandom-valued impulse noise of density 50% using differentdenoising techniques.

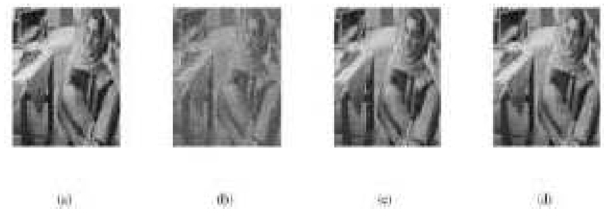

Fig.1. Performance of various methods on Barbara image (a) Original Image, (b) Image corrupted by 50% Random-valued impulse noise, (c)SDROM filter output, (d) ACWMF output.

Patch Size in the Data Term: The size of the patch Ψ in thedata term helps to capture the local image characteristicsaround the boundary of the hole, and get a good continuationof the image structure and texture. The practical rule: Fix thesize of the patch for images at lowest resolution and increaseslinearly the size when doubling the resolution in eachdimension. In practice, the lowest resolution image sizeconsiders around 80 × 80 for which it uses a patch of size 7×7.As an example, when the image size is 1000 × 1000, the patch
size is 17 × 17. Figure 2 illustrates how the choice of patchsize affects the quality of the in painting 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 multiscalealgorithm is set using the rule: consider one level of resolution for images of size a × b and then adds the additionallevel when doubling the resolution in every dimension.
3) Search Range: For computational efficiency, set a restrictedsearch range around the hole, specifying it by a bound on themaximum offset.

V. PROPOSED METHEDOLOGY

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

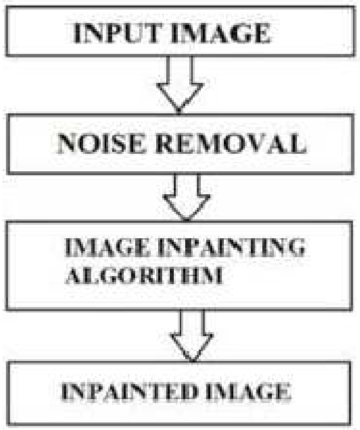

Fig. 3.Steps for proposed method

Noise Removal:

Adaptive Median Filter (AMF) perform well at low noisedensities. But at high noise densities the window size has to beincreased 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 arobust decision is difficult. Also these filters will not take intoaccount the local features as a result of which details and edgesmay 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 valueis 0 or 255 it is processed else it is left unchanged. At highnoise thickness the median value will be 0 or 255 which isnoisy. In such case, neighboring pixel is utilized forreplacement.

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 inpaintingtechniques, 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 simpleupdate rule allows measuring the relative confidence ofpatches on the fill front, without image specific constraints. As
filling proceeds, confidence values decay, indicating that lesssure of the color values of pixels near the centre of the targetregion.

VI.Conclusion& Future Work

This paper proposed a method for detection and removal ofthe noise & algorithm for removing large objects from digitalphotographs. The outcome of object removal is an image inwhich the selected object has been replaced by a visuallyplausible background that mimics the appearance of the sourceregion. Pixels maintain a confidence value, which collectivelywith image isophotes, influence their fill priority. When thesearch range is too small one does not capture enough similarpatterns. Currently, investigating extensions for more accuratepropagation of curved structures in still photographs and forobject removal from images, which promise to impose anentirely new set of challenges.

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