RESEARCH ARTICLE OPEN ACCESS

Optimal Sparse Representation Based Robust Image Inpainting

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Abstract –
Image inpainting is recovery of missing pixels.Inpainting methods use the information of the known image areas in order to fill the gap .Original image contain duplicate information. The aimis to remove the duplicated information from the original image. But sometime some pixel and image quality can be removed. The new image inpainting model which is formulated using the smoothed and weighted l1 normof the coefficients of the underlying image under a given redundant system. The redundant system is generated by the DCT-Haar multi resolution analysis. The developed algorithm based on simulated annealing method. This algorithm is updated based on the local information of the coefficients of the solution in iterations. It is mainly used for compute optimal weight value sparse representation. The DCT as an orthogonal transform is used in various applications. The row of a DCT matrix filters associated with a multi resolution analysis. Nondecimate wavelet transforms with these filters are explored in order to analyze the images to be in painted.The redundant system generated by the DCT-Haar multi resolution analysis suitable for inpainting problems including impulsive noise removal and filling missing information over regions with moderate sizes.
Index Terms—L1minimization, discrete cosine transform, simulated annealing, inpainting.

I. INTRODUCTION

Inpainting is rooted in the restoration of images. Inpainting is the process of reconstructinglost or deteriorated parts of images and videos. Traditionally, inpainting has been done by professional restorers. The underlying methodology of their work is as follows: The global picture determines how to fill in the gap. The purpose of inpainting is to restore the unity of the work. The structure of the gap surroundings is supposed to be continued into the gap. Contour lines that arrive at the gap boundary are prolonged into the gap. The different regions inside a gap, as defined by the contour lines, are filled with colors matching for those of its boundary. The small details are painted, i.e. texture is added.

In many applications, only partial data are available in an image due to a variety of reasons including impulsive noise caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, transmission in a noisy channel, text or signature superposed on an image, and a scratch in a picture. Recovery of missing pixels is called image inpainting, an active area of research in image processing. Applications of image inpainting include old film restoration, video inpainting, de-interlacing of video sequences, and cloud removal from remotely sensed images. Restoring missing pixels becomes indispensable in the above applications.

Fig.1: Image Inpainting

Many successful algorithms for image inpainting have been developed in the past decade. These inpainting algorithms can be roughly classified into three groups: geometric partial differential equation (PDE), patch, and sparse representation. Within the category of PDE-based methods, there are a number of approaches which perform well for piecewise smooth images with sharp edges. Patch-based inpainting methods fill in missing pixels of an image from known non-local observed data by exploring local repetitions of local information. Sparse representation for image inpainting was recently addressed, and the references therein. The main idea of these algorithms is to sparsely represent an image by a redundant system which is formed by a set of transforms such as the discrete cosine transforms wavelets. The missing pixels are then inferred by shrinking coefficients adaptively and iteratively from this sparse representation.

II. PREVIOUS WORKS

Image inpainting algorithms include geometric partial differential equation (PDE), patch, and sparse representation based ones. Methods for image inpainting use PDEs and variational formulations to propagate available image information from observed domains into missing regions as a way of smoothly transporting the contours of the image into the regions being inpainted. Patch-based inpainting methods fill in missing pixels of an image from known non-local observed data by exploring local repetitions of local information. Algorithms in this category propagate the known patches into missing patches gradually in a fashion of cut-and-paste, especially for missing regions with texture and large sizes. Sparse representation for image inpainting was recently addressed in Spline Framelet based (SF), Spline Framelet and Local DCT based (SF-LDCT), and Morphological Component Analysis based (MCA). The main idea of these algorithms is to sparsely represent an image by a redundant system which is formed by a set of transforms such as the discrete cosine transform, wavelets, framelets, and curvelet.

1) Approach for missing data recovery

An iterative algorithm based on tight framelets for image recovery from incomplete observed data. The algorithm is motivated from our framelet algorithm used in high-resolution image reconstruction and it exploits the redundancies in tight framelet systems. The convergence of the algorithm and also give its convergence factor. The minimization properties of the algorithm and explore the roles of the redundancy of tight framelet systems.

2) Exemplar-Based Image Inpainting

A new algorithm is proposed for removing large objects from digital images. The challenge is to fill in the hole that is left behind in a visually plausible way. The 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 precedes. A best-first algorithm, in which the synthesized pixel valuesconfidence is propagated in a manner similar to the propagation of information in inpainting. The actual color values are computed using exemplar-based synthesis.

3) Bandelet-Based Inpainting

An efficient inpainting technique for the reconstruction of areas obscured by clouds or cloud shadows in remotely sensed images is presented. This technique is based on the Bandelet transform and the multiscale geometrical grouping. It consists of two steps. In the first step, the curves of geometric flow of different zones of the image are determined by using the Bandelet transform with multiscale grouping. This step allows an efficient representation of the multiscale geometry of the image's structures. Having well represented this geometry, the information inside the cloud-contaminated zone is synthesized by propagating the geometrical flow curves inside that zone. This step is accomplished by minimizing a functional whose role is to reconstruct the missing or cloud contaminated zone independently of the size and topology of the inpainting domain.

4) Bandelet Transform with Multiscale Grouping

The multiscale grouping uses a multiscale association field in order to group together coefficients in the direction specified by the flow. These recursive groupings allow one to take into account junctions and long range regularities of remotely sensed images. The multiscale grouping is first computed by applying the Haar transform over pairs of points that are neighbors according to an association field. The role of this field is to group together points that have similar neighborhoods in order to exploit the geometry of the signal. Then, a weighted mean and a weighted difference are computed between the values of the signal that are grouped together. The means and differences are consequently stored, and the process of computing the associated field and the Haar transform is repeated iteratively by doubling the scale at each step. This iterative process decomposes the original image in an orthogonal basis called grouping basis.

III. PROPOSED METHOD

Image inpainting model is formulated using the smoothed and weighted l1 normof the coefficients of the underlying image under a given redundant system. The redundant system is generated by the DCT-Haar multi resolution analysis. The developed an algorithm based on simulated annealing method.The algorithm is updated based on the local information of the coefficients of the solution in iterations. It is mainly used for compute optimal weight value sparse representation. The DCT as an orthogonal transform is used in various applications.

Inpainting is the process of reconstructing lost part of images based on the background information. Image Inpainting fills the missing or damaged region in an image utilizing spatial information of its neighboring region. It is helpfully used for restoration of old films and object removal in digital photographs. The main objective is to efficiently remove the impulsive noise and to reduce the time.It also provide a better image quality with lower complexity and also improve the processing speed and PSNR value.

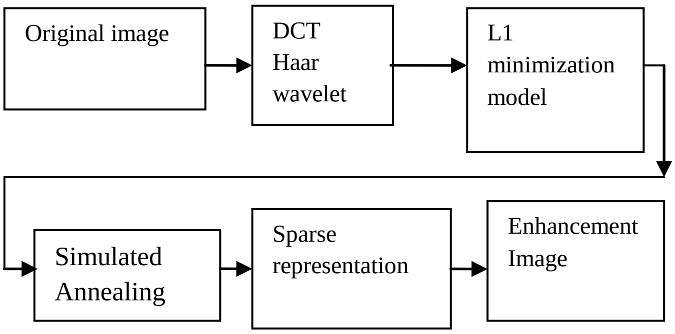

Fig 2: Architecture diagram

The Figure 2 shows architecture diagram. Recovery of missing pixels is called image inpainting, an active area of research in image processing.Inpainting methods use the information of the known image areas in order to fill the gap.The color image is converted into gray scale image and image is divide into an overlapping map. DCT Haar wavelet is a multiresolution analysis. It is used to extract the DCT Haar features. Then apply the L1 minimization model. Find the optimal weight value using simulated annealing algorithm. In Sparse representation is used same regions are replaced. Finally the noise is removed in the image and filling missing information over region with moderate sizes.

1)DCT-Haar wavelet

Inpainting model is formulated as an optimization problem in which the variational objective functional has a regularization term formed by a sparse representation of the underlying image. The proposed optimization model is connected with the reweighted L1 minimization model, but with several distinct and promising properties.

Let f_{org} the original image be defined on the domain Ω = {1, 2... n} and a nonempty proper subset D of Ω be given. The observed image g is modeled as

$$g[k] = \begin{cases} forg[k], k \in \Omega \backslash D \\ h[k], k \in D \end{cases} \qquad (1)$$

Where h[k] with k ∈ D could represent any types of degradations to the original image including impulsive noise and texts superposed on f_{org}. Associated with the sets Ω and D, we define an n × n diagonal matrix, denoted by PD, whose k^{th} diagonal entry is 1 if k ∈Ω \ D and 0 if k ∈D. The goal of image inpainting is to seek an image f such that P_{Df}= P_{Dg} while f can truthfully retain original information of f_{org}.

Discrete cosine transforms are frequently used orthogonal transforms in applied mathematics and engineering. Among various types of the DCTs, the discrete cosine trans-form of second type DCT-II is the most popular one of all and will be chosen below in our discussion.

The standard m × m DCT-II matrix C is

$$c := \frac{1}{m}\left[\in_k \; cos\frac{(k-1)(2j-1)\pi}{2m} : k, j = 1,2, \dots m\right](2)$$

Where$\in_1 = 1$ $\in_k = \sqrt{2}$ for k=2,3,…,m.The matrix C is orthogonal, i.e., $C^TC = I$. Denoting by c_k the k -th row of $\frac{1}{\sqrt{m}}C$. It can directly verify that the sum of entries of c_k is 1 for k = 1 and zero fork = 2, 3,..., m. Hence, the vector c1 can be viewed as a low-pass filter and others can be viewed as high-pass filters. In particular, when m = 2, c_1 and c_2 are low-pass and high-pass filters corresponding to thewell-known Haar multiresolution analysis. $c_1$and c_k, k = 2 , 3 ,...,m , from a general m × m DCT-II matrix, are the low-pass and high-pass filters associated with a multiresolution analysis .

2) L1 minimization model

It is possible to reconstruct sparse signal exactly from highly incomplete sets of linear measurement and that can be done by constrained L1 minimization. To solving a sequence of weighted L1 minimization problems where the weights used for the next iteration are computed from the value of current solution.

The method is applied to recover the signals with assumed near sparsity in over complete representation not by reweighting the L1 norm of the coefficient sequence is common, but by reweighting the L1 norm of the transformed object.

Larger coefficients are penalized more heavily in the l^1 norm than smaller coefficients, unlike the more democratic penalization of the l^0 norm, it was proposed to consider the “weighted” l^1 optimization problem

$$min\|T_x\|_{1\; subject\;\; to\; y=\Phi x} \qquad (3)$$

Where T is a diagonal matrix with positive numbers t [1] , ...,t [q] on its diagonal.

3) Simulated Annealing

SimulatedAnnealing(SA)is a generic probabilistic metaheuristic for the global optimization problem of locating a good approximation to the global optimum of a given function in a large search space. The main steps of the basic SA algorithm:

Step 1: Generate an initial solution S

Step 2: Choose a solution S'€ N(S) and compute the difference in the object value ΔC(S)-C(S')

Step 3:If

(i) S' is better than (SΔ>0), or

(ii) $\delta \geq e^{\Delta/T}$

Then replace S by S'(S←S')

Else retain the current solution

Step 4: Update the current temperature

Step5: If an stopping criterion is satisfied STOP,ElseGOTO Step 2

In order to use the algorithm for a problem, important factors that must be taken into consideration when making choices falls into 2 classes:

a) Problem-specific choices: representation of possible solutions, definition of the cost function, and the generation mechanism for the neighbors.

b) Generic choices for cooling schedules: the initial value of the temperature, the cooling rate and the temperature update rule, the number of iterations to be performed at each temperature, and the stopping criterion.

Simulated annealing algorithm of the data processing produce and receive can be divided into below four steps:

(i)The first step is produced from the current solution by using the cost function

(ii)The second step is to computing and data processing of the correspondingobjective function difference. Because of the target function only difference by transform part production, so the objective function calculated according to the difference of the best incremental calculation.

(iii)The third step is to judge whether the data processing is accepted. The most commonly used accept rule is Metropo1is criteria: if Δ t '< 0 is accepted as a new' S current solution S, or otherwise the probability exp (- Δ t '/ t) accept S' as a new current solution S.

(iv)The fourth step is when the data processing is determined to accept and current solution continuing to the next round of test, the use of data processing to replace the current solution, this just the current solution corresponding to express in produce the transform part to achieve, and at the same time, the objective function value can be modified. At this time, the current solution implements iteration.

4) Sparse representation

Variational objective function has a regularized term from a underlying image. The missing pixels are then inferred by shrinking coefficient adaptively and interactively from sparse representation. Recover the sparse representation of a target image and the image plane transformation between the target and the model images.

5) Enhancement image

Enhancement image is the process of adjusting digital images so that the results are more suitable for display.To make an image lighter or darker, or to increase or decrease contrast. Contrast enhancement improves the visual quality of an object. It should be enhancing the brightness difference between objects and their backgrounds. It also improves the perceptibility of objects. In general, the enhancement techniques for dimmed images can be broadly divided into two categories: direct enhancement methods and indirect enhancement methods. In direct enhancement methods, the image contrast can be directly defined by a specific contrast term. However most of these metrics cannot simultaneously gauge the contrast of simple and complex patterns in images which contain. Conversely, indirect enhancement methods attempt to enhance image contrast by redistributing the probability density.

IV. EXPERIMENTAL RESULTS

The experimental result shows the numerical result to demonstrate the performance of proposed inpainting algorithm. The problem of removing impulsive noise can be viewed as one image inpainting. Three impulsive noise levels namely 30%, 50%, 70% are used to test robustness and efficiently of the proposed algorithm. The experimental result with SF, SF-LDCT, MCA, and APDG are reported in Table I

TABLE I
REPRESENTS THE PSNR AND THE CPU TIME

Algorithm	Lena	Barbara	Case
SF	(28.44,316)	(26.13,264)	
SF-LDCT	(27.69,577)	(28.37,540)	70%
MCA	(27.85,92)	(29.11,92)	
SA	(25.64,78)	(31.32,78)	
SF	(31.34,205)	(26.77,185)	
SF-LDCT	(30.70,372)	(32.60,320)	50%
MCA	(31.09,84)	(32.67,85)	
SA	(29.67,76)	(30.89,74)	
SF	(34.96,147)	(34.49,142)	
SF-LDCT	(34.01,246)	(37.30,264)	30%
MCA	(35.33,106)	(37.99,108)	
SA	(31.45,100)	(35.45,99)	

In this table shows improvements made by APDG over the other three algorithms. The visual comparison of the inpainted images by SF, SF-LDCT, MCA, and SA are presented for the images of Lena and Barbara corrupted by impulsive noise with noise level of 70%.

Fig 3: Inpainted Images

In Figure 3 present the inpainted images using these four algorithms. It can observed all the algorithm can inpaint the images well but SA is the best of them in terms of the inpainted images

V. CONCLUSION

An image inpainting model is formulated using the smoothed and weighted L1 norm of the coefficients of the underlying image and the redundant systems generated by the DCT-Haar multiresolution analysis. An algorithm is based on simulated annealing method. The weight matrix in the proposed algorithm is updated based on the local information of the coefficients of the solution in iterations. The proposed algorithm outperforms the three state-of-the-art alternatives for various examples in terms of both PSNR values and visual quality of the experimental results. The redundant system generated by the DCT-Haar multiresolution analysis and the resulting inpainting model are particularly suitable for inpainting problems including impulsive noise removal and filling missing information over regions with moderate sizes.

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