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An Enhanced Primal-Dual Vertex Cover (EPDVC) Method for TotalVariation Based Wavelet Domain Inpainting

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Abstract:

Inpainting is the process of reconstructing lost or deteriorated parts of images. In the digital world, inpainting (image interpolation) refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image data (mainly small regions or to remove small defects). Recently various methods have been proposed to tackle the inpainting problem. But they had their own disadvantages, but one of the best methods chosen for inpainting problem is "primal–dual method for total variation-based wavelet domain inpainting", but it takes more number of iterations, to overcome this problem we propose an efficient scheme called "An Enhanced Primal-dual vertex cover (EPDVC) method for total variation-based wavelet domain inpainting ".

Keywords:
Inpainting, Total Variation, Wavelet Transform, Primal-Dual.

I. INTRODUCTION:

Image inpainting is a technique of filling in the missing region of an image[7]. The main usage of inpainting is in restoring damaged part of the picture entire picture the receiver can still recover missing part of the image to come up with the whole image in the end. We can think of the transmitter intentionally not sending certain block of image and the receiver filling in the missing region upon reception of the incomplete picture. By not sending significant portion of the picture that can later be restored from remaining part, we can significantly reduce the amount of bits needed to transmit the image.

For this method to be successful, it is important to choose and erase the block that can be easily restored. There are two types of regions that can be relatively easily reconstructed, structure and texture. It is also important to properly classify these blocks into either of these two.

As this method presupposes that missing blocks can be accurately recovered by appropriate inpainting algorithm, careful attention should be paid to the inpainting algorithm for each type of blocks. The aim of wavelet domain inpainting is to reconstruct the wavelet coefficients of original image using the given wavelet coefficients. It is well-known that the inpainting [7] problem is ill-posed, i.e. it admits more than one solution.

There are many different ways to fill in the missing coefficients, and therefore one may have different reconstructions in the pixel domain. A regularization method can be used to fill in the missing wavelet coefficients.

Numerous methods have been proposed to solve saddle point [9] problems. They include the finite envelope method, the primal–dual steepest descent algorithm, the alternating direction method, primal dual iteration algorithm and so on each of them has its own advantages and disadvantages.

In the above primal dual iterative algorithm is suited to solve but the main difficulty & disadvantage arises from the forward & backward wavelet transformation, the gradient operation & the divergence operator, which causes a lag-city-of-time. Therefore in this paper we demonstrate a simple & efficient algorithm called (EPDVC) to solve the above problem.

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II. Total Variation:

In signal processing, Total variation denoising, also known as total variation regularization is a process, most often used in digital image processing, that has applications in noise removal. It is based onthe principle that signals with excessive and possibly spurious detail have high total variation that is, the integral of the absolute gradient of the signal is high. According to this principle, reducing the total variation of the signal subject to it being a close match to the original signal, removes unwanted detail whilst preserving important details such as edges. The total variation[7]denoising algorithm is to include inpainting, i.e., the process of filling in missing or damaged parts of a (possibly noisy) image. The basic idea is still to compute a reconstruction that is "smooth" in the TV sense, and identical to the data in all the non-corrupted pixels. Specifically, let I be the index set for x corresponding to the corrupted pixels in X. The complementary index set Ic is the set of noncorrupted pixels. The basic TV inpainting problem can then be formulated as

$$\text{Minimize } \sum_{i=1}^{m}\sum_{j=1}^{n} \|D(ij)x\|_2$$
$$\text{Subject to } \|(x-b)I_c\|^2 \leq \delta$$

In digital image processing, an image is represented by a matrix or by a vector formed by stacking up the columns of the matrix. In the latter representation of an image, the n×n pixel becomes the (r,s)thpixel becomes the((r -1)n+s) entry of the vector. The acquired image g is modeled as the original image f plus an additiveGaussian noise η. i.e.

g=n+η

In the following, it is denoted by fr,s the ((r -1)n+s)th entry of fin the JPEG 2000 format, images are transformed from the pixel domain to a wavelet domain through a wavelet transform. Wavelet coefficients of an image under an orthogonal wavelet transform W are designated by ^.Thus, the wavelet coefficients of the noisy image g are given by

g^=w^

The observed wavelet coefficients are given by g but with the missing ones set to zero, i.e., u ^ Then, an observed imageu ^ is obtained by the inverse wavelet transform

u=WTu ^

The aim of wavelet-domain inpainting is to reconstruct the original image f from the given coefficients u ^. To fill in the corrupted coefficients in the wavelet domain in such a way that sharp edges in the image domain are preserved, Chan et al. proposed the following in to minimize the objective function.

$$j(f) = 1/2 \sum_{i\in I}(\hat{f}_i - \hat{u}_i)^2 + \lambda\|f\|_{TV}$$

where

$$\lambda\|f\|_{TV} = \sum_{r,s\in\Omega}(|(D_x f)_{r,s}|^2 + |(D_y f)_{r,s}|^2)^{1/2}$$

is the TV norm, Dz is the forward difference operator in the z-direction for z fx, yg, and is a regularization parameter. This is a hybrid method that combines coefficients fitting in the wavelet domain and regularization in the image domain. A number of numerical methods have been proposed for solving TV minimization problems in the primal[11,9] setting. They include

1. Time marching scheme.

2. Fixed-point-iteration method.

3. Majorization-Minimization approach and many others.

In this paper, we are introducing the majorizationminimizationapproach for solving TV minimization problem.

III. An Enhanced Primal-Dual Vertex Cover (EPDVC):

We have seen many algorithms based on linear program (LP) relaxations, typically involving rounding a given fractional LP solution to an integral solution of approximately the same objective value. In this article, we will look at another approach to LP relaxations, in which we will construct a feasible integral solution to the LP from scratch, using a related LP to guide our decisions.

Our LP will be called the Primal LP, and theguiding LP will be calledthe Dual LP. As we shall see, the PD method is quite powerful. Often, we can use the Primal- Dual (PD)[11] method to obtain a good approximation algorithm, and then extract a good combinatorial algorithm from it. Conversely, sometimes we can use the PD method to prove good performance for combinatorial algorithms, simply by reinterpreting them as PD algorithms.Before we get to primal-dual algorithms, observe that strong duality is useful as a min-max relation. In fact many min-max [13]relations can be proven from it relatively easily.

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For example, Von Neumann's minimax theorem follows easily from it. The max-flow/min-cut theorem also falls right out of LP duality, if you realize that the natural max flow LP is dual to the natural min-cut LP and the min-cut LP has integral basic feasible solutions. We will prove another minmax relation using the Weak Duality Theorem and the dual LP for Vertex Cover.

Then integral solutions to VC-Dual-LP correspond exactly to matching's in the input graph. Thus, by weak duality, we conclude that the minimum vertex cover in an unweighted instance is at least the size of the maximum cardinality matching in the input graph. That is, in non-decreasing order of cost, we have the maximum cardinality matching (equal to VC-Dual-IP-OPT), VC-Dual-LP-OPT, VC-LP-OPT, and finallyVC-IP-OPT (equal to the Vertex Cover OPT).

IV. NUMERICAL RESULTS:

Here we report some experimental results shown in below figures 1,2 & 3 to illustrate the performance of the proposed approach .The experiments were performed under widowsXP and MATLAB(R2012b) running on a desktop machine with an intel core 2 Duo central processing unit at 2.67GHz AD 3gb of memory.

In order to reduce the size of an image,the JPEG 2000 standard can reduce the resolution automatically through its multi-resolution decomposition structure. The wavelet coefficients[7] of all high frequency sub bands are discarded,and only that of low frequency sub bands are kept.

Fig 1: Original image and inpainted image

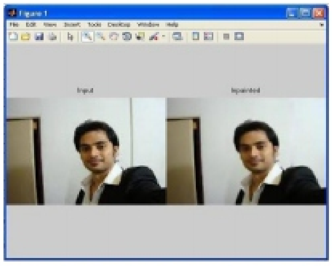

Fig 2: Original image and inpainted image

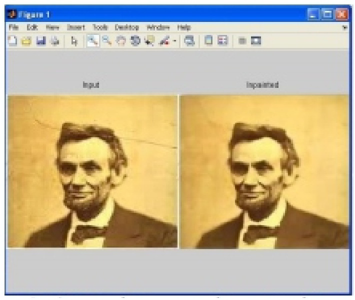

Fig3: Original image and inpainted image

V. CONCLUSION:

In this paper, a novel approach for removing scratches and text from contaminated images has been presented. The proposed technique use EPDVC method in a way that removes unwanted regionsfrom image which is known as image inpainting. Experimental results reveal that the proposed technique having less number of iterations compared to existing technique.

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