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Image Denoising using TWIST Method

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Abstract: *Most advancement in image de-noising algorithms are involving relatively poor numbers of patches and exploiting its similarity. These patch-based methods are completely based on matching of patches and their performance is restricted by the ability to dependably find suitably parallel patches. As number of patches grows, studies show that a point of retreating returns is reached where the performance enhancement due to more patches is counteracting by the lower possibility of discovery sufficiently close similarity. Based on our study the net conclusion is that as patch based methods, such as BM3D, are shining largely, they are eventually restricted in how well they can do on (superior) images with rising obstacle. Thus our attempt in this work is to deal with these complications by formulating a prototype for accurately universal filtering wherever each pixel is projected from all pixels in the image. After analyzing all the previous works, our objective is dual. Initially, our attempt is to give an analysis based on statistics of our planned universal filter, which is strictly based on matching operative's spectral disintegration, and we learn the outcome of truncation of this spectral disintegration. Subsequently, we obtain an estimate to the spectral (prime) mechanism using the Nystrom extension. Using these, we exhibit that this universal filter can be applied proficiently by sampling a moderately miniature percentage of pixels in our image. Studies demonstrate that our approach can successfully take any existing de-noising filters universally to approximate each pixel with every pixel in the image, consequently enhancing upon the finest patch-based method.*
Keywords: *Eigen decomposition, Iteration,TWIST method*

I. Introduction

Noise reduction is the method of removing noise from a signal. Every recording device, analog or digital, has character which makes them susceptible to noise. White noise (random) without coherence introduced by the device's mechanism or processing algorithms. Within electronic recording devices, hiss is the key form which is caused by unsystematic electrons that, profoundly influenced by temperature, stray from their selected course. Stray electrons influence the voltage of the output signal and therefore make noticeable noise. For photographic film and magnetic tapes, noise (audible and visible) is due to the grain composition of the standard. For photographic film, the extent of the grains in the film determines the film's sensitivity, more sensitive film having big sized grains. For magnetic tapes, the big the grains of the magnetic particle (commonly magnetite), the more prone the standard is to noise. Compensating for this, big areas of film or magnetic tape may be used to lesser the noise to an adequate stage.

Image de-noising is a key image processing job, both as a method itself, and as an element in other methods. Very many methods to de-noise an image or a set of data exist. The main features of a good image de-noising model are that it will remove noise while saving edges. Conventionally, linear forms have been used. Among those one widespread method is using Gaussian filter, or equivalently solving the heat equation using noisy image as input data, which is a linear,second order PDE-model. In some functions this type of de-noising is sufficient. Out of many, one benefit of linear noise elimination models is swiftness. Drawback of the linear models is that they are unable to safeguard edges in a superior way: boundaries, which are realized as discontinuations in the image, are smeared out. On the other hand, non-linear models can hold edges to a great extent than linear model. For nonlinear image de-noising, one of the famous method is the Total Variation (TV)-filter, introduced by Rudin, Osher and Fatemi, which is very superior at conserving edges, but smoothly varying regions in the input image by transferring into piecewise constant regions in the output image. Using TV-filter as a de-noiser leads to solving a second order nonlinear PDE. As smooth regions are changed into piecewise constant regions by means of the TV-filter, it is desirable to make a model for which smoothly varying regions are changed into smoothly varying regions, and yet the edges are conserved. This can be done for occasion by solving a fourth order PDEd instead of the second order PDE from the TV-filter.

II. Related Work

A spatial domain de-noising process has a transform domain filtering interpretation, where the orthogonal basis elements and the shrinkage coefficients are respectively the eigenvectors and eigenvalues of a symmetric, positive definite (data-dependent) filter matrix. For filters such as NLM and LARK the eigenvectors corresponding to the dominant eigenvalues could well represent latent image contents. Based on this idea, the

SAIF method [1] was recently proposed which is capable of controlling the de-noising strength locally for any given spatial domain method. SAIF iteratively filters local image patches, and the iteration method and iteration number are automatically optimized with respect to locally estimated MSE. Although this algorithm does not set any theoretical limitation over this local window size, computational burden of building a matrix filter for a window as large as the whole image is prohibitively high.

Williams and Seeger [2], the Nystrom method [3] gives a practical solution when working with huge affinity (similarity) matrices by operating on only a small portion of the complete matrix to produce a low-rank approximation. The Nystrom method was initially introduced as a technique for finding numerical solutions to eigen decomposition problems in [3] and [4]. The Nystrom extension has been very useful for different applications such as manifold learning [5], image segmentation [6], and image editing [7]. Fortunately, in our global filtering framework, the filter matrix is not a full-rank local filter and thus can be closely approximated with a low-rank matrix using the Nystrom method.

Our contribution to this line of research is to introduce an innovative global de-noising filter based on twist method, which takes into account all informative parts of an image .

III. Proposed Solution

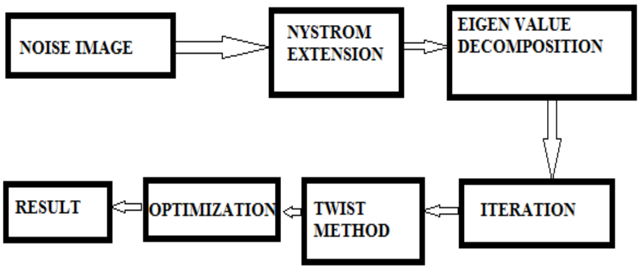

Figure1: Block Diagram

A. Noisy image:

It is considered as input image and it involves more noise inside of image. So this image is taken for denoising.

Image format: '*.jpg','*.png' etc..

The type of noises are Gaussian noise, Salt-and-pepper noise, Shot noise and Quantization noise (uniform noise)

i. Gaussian noise

Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the standards that the noise can acquire on are Gaussian-distributed.

ii. Salt-and-pepper noise

Salt-and-pepper noise is a form of noise sometimes seen on images. It presents itself as meagerly taking place white and black pixels. An capable noise reduction process for this type of noise is a median filter or a morphological filter.

iii. shot noise:

Shot noise has a root-mean-square value proportional to the square root of the image strength, and the noise at different pixels is independent of one another. Shot noise has a Poisson allocation, which is usually not very different from Gaussian.

iv. Quantization noise

The noise caused by quantizing the pixels of a sensed image to a number of discrete levels is known as quantization noise. It has an roughly consistent distribution. Though it can be signal reliant it will be signal free. If further noise sources are big enough to cause wavering, or if wavering is explicitly applied.

B. Nystrom Extension

This method allows extrapolation of the complete grouping solution using only a small number of typical samples.

Let $g : [0, 1] \times [0, 1] \rightarrow R$ be an SPSD kernel and (u_i, λ_i^u),
$i \in N$, denote its pairs of eigen functions and eigenvalues:

$\int_0^1 g(x,y)Ui(y)\,dy = \lambda_i^u u_i(x),\ i \in N.$

The Nystr¨om extension approximates the eigenvectors of g(x, y) by evaluation of the kernel at k^2 distinct points

Let $\{(x_m, x_n)\}^k_{m,n}=1 \in [0, 1] \times [0, 1]$.

Define $G(m, n) \equiv G_{mn} := g(x_m, x_n)$

$\frac{1}{k}\sum_{k=1}^{n} G(m,n)vi(n) = \lambda_i^v v_i(m), i=1,2,\ldots k$

where (vi, λ_i^v) represent the k eigenvector-eigenvalues pairs associated with G.

only use partial information about the kernel to solve a simpler eigenvalue problem, and then to extend the solution using complete knowledge of the kernel.

The Nystrom extension has been helpful for diverse purposes such as

a. manifold learning
b. image segmentation and
c. image editing .

Fortunately, in our global filtering framework, the filter matrix is not a full-rank local filter and thus can be closely approximated with a low-rank matrix using the Nystrom method

C. Eigen value decomposition

The eigen values play an important role in image processing applications. There are various methods available for image processing. This dealing out with measurement of image sharpness can be done using the concept of eigen values. Also, the classification of image such as coin and face is done using an eigen-space approach. In this, the eigen values are calculated using the singular value decomposition (SVD).

D. Iteration

Decomposition values done through this eigen value models. Collecting of this values goes an continue process(iteration) and makes real factors for original images. Generally iteration process makes in 'for loop' in MATLAB

E. TWIST Method

Many approaches to linear inverse problems define a solution (*e.g.*, a restored image) as a minimizer of the objective function

$$F(x)=\frac{1}{2}\,\|y-Kx\|^2 + \lambda\varphi(x)$$

where y is the observed data, K is the (linear) direct operator, and F(x) is a regularizer. The intuitive meaning of f is simple: minimizing it corresponds to looking for a compromise between the lack of fitness of a candidate estimate x to the observed data, which is measured by $\|y-Kx\|^2$, and its degree of undesirability, given by F(x). The so-called regularization parameter l controls the relative weight of the two terms.

State-of-the-art regularizers are non-quadratic and non-smooth; the total variation and the ℓp norm are two well known examples of such regularizers with applications in many statistical inference and signal/image processing problems, namely in de-convolution, MRI reconstruction, wavelet-based de-convolution, Basis Pursuit, Least Absolute Shrinkage and Selection Operator (LASSO), and Compressed Sensing

Iterative shrinkage/thresholding (IST) algorithms have been recently proposed to the minimization of f, with F(x) a non-quadratic, maybe non-smooth regularizers. It happens that the convergence rate of IST algorithms depends heavily on the linear observation operator, becoming very slow when it is ill-conditioned or ill-posed. Two-step iterative shrinkage/thresholding TwIST algorithms overcome this shortcoming by implementing a nonlinear two-step (also known as "second order") iterative version of IST. The resulting algorithms exhibit a much faster convergence rate than IST for ill conditioned and ill-posed problems.

IV. Conclusion And Results

In this paper a TWIST method based filter has been developed using MATLAB. In this system, firstly pre-processing of the image is done and then these pre-processed image is added with some amount of noise. This noisy image is fed to Nystrom extension, then perform eigen decomposition. Then perform iteration process. After that apply the twist method to the processed image, then get the noise removed image. The various steps are shown in the below figures.

TWIST method is a very efficient and time consuming method compared to existing methods.

Fig 2: Input image **Fig 3:**image with noise

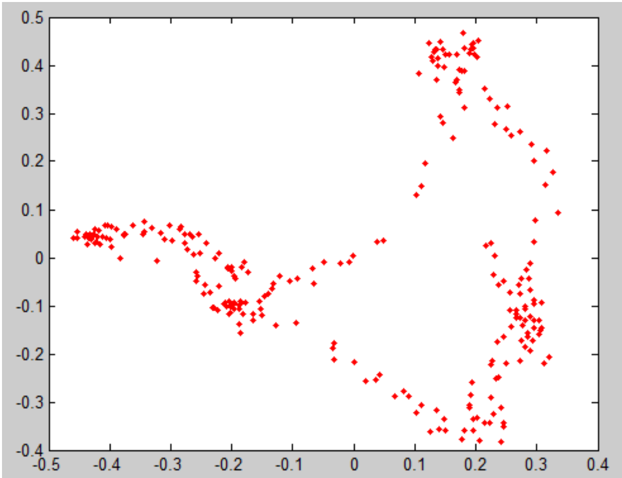

Fig 4: histogram of noisy image

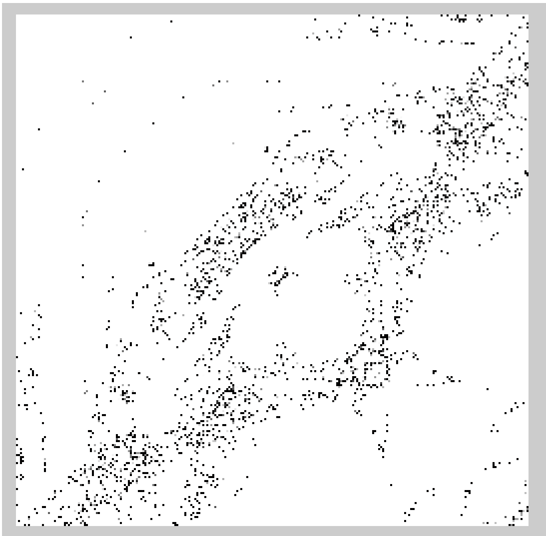

Fig 5: Image after Iteration

Fig 6: [a]First step [b]Second step (reduced noise)

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