ISSN 2394-3777 (Print)
ISSN 2394-3785 (Online)
Available online at www.ijartet.com
International Journal of Advanced Research Trends in Engineering and Technology (IJARTET)
Vol. 4, Special Issue 10, March 2017

Image Denoising Using BM3D-Sparse Representation On 2-D Images

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***Abstract*— Images are susceptible to noises during acquisition, compression and transition. As image processing plays a significant role in medical field, remote sensing, pattern recognition, color/video processing and segmentation it require image denoising as a pre-processing step. Many denoising algorithms are prone to low SNR, edge preservation, coarse grain noise which is explored by implementation of BM3D. Since sparse representation shows promising results in space consumption and fast computation, it is been implemented along with block matching. The results shows that for different noise value the estimates of PSNR value increases proving its efficiency close to the optimal performance. The scope of this paper can be extended to different image by training them with the appropriate data set.**

Keywords—tv-total variation, bm3d-blockmatching, sr-sparse representation.

I. INTRODUCTION

Image processing systems already have advanced significance in the past years and played an extremely important role in our society and the demand for the high quality image is increasing exponentially, requiring more techniques in image denoising. Data sets collected by image sensors are generally contaminated by noise. This means pixels that are not representing the colour, or the exposure of the original image. The removal of noise from the image so as to make it corrupt free and preserve the fine details is known as ―Image Denoising. There are various methods but identifying the type of noise and denoising technique is important.

The different types of noises that can be found on digital images are Gaussian Noise, Speckle Noise, Poisson Noise, Salt & Pepper Noise, Shot Noise, and Quantization/Uniform Noise. There are many techniques practiced to denoise the image but the selection of suitable technique for particular application is a challenging task. The main property of the image denoising model is to denoise without damaging the edges.

The demand for the less computation time and storage arises as it follows intricate calculation procedure. To overcome the situation, we handle sparse technique. In sparse technique the number of elements of the matrix representation of an image has lot of zero entries than non zero entries. Generally sparse technique is applied when the image is not densely packed. Conceptually, sparsity corresponds to systems which are loosely packed. Any N-node graph can be represented as a NxN sparse matrix, where each row corresponds to a node and each column represents a link between the node to any other node in the graph. It is the ratio of total zero valued elements to the total elements. Common applications for sparse matrices are in solving the partial differential equations by Finite Element Models, computer graphics, machine learning, information retrieval and large scale application. The sparse matrix can be constructed by DOK (dictionary of keys),LIL (list if lists),COO (coordinate lists). Thus the exploitation of sparsity helps in time and space storage.

Thus the objective of this paper is to denoise the given 2D image by making use of the block matching 3D algorithm. Generally image is comprised of many self repetitive similar elements. By finding those similar patches, they can be grouped and denoised. This is realized by three steps. Firstly grouping of the similar 2D blocks into groups which is 3D data arrays. Secondly these blocks undergo 3D transforms, filtering (in order to attenuate higher noise levels) in order to preserve the fine details and features of individual blocks and its inverse. Since it results different estimates for each pixel as they are overlapping, these blocks have to be combined. The aggregation is a similar to the averaging procedure. These steps are repeated again with this basic estimate and finally the total estimate is estimated.

This paper is organized as follows. Section II presents analysis of related denoising algorithms. Section III formulates BM3D denoising algorithm. Section IV deals with the results whereas conclusion are reported in section V.

II. ANALYSIS OF DENOISING ALGORITHMS

The denoising is a demanding task and basically the real problem is to estimate a true signal from the noisy version.

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The overall goal of this section is to establish the significance of the general field of study, and to identify a place where a new contribution could be made. The bulk of this chapter was on critically evaluating the different methodologies used in this field so as to identify the appropriate approach to use in our project.

A.Total Variation Method

The 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 will make the signal similar to the original signal, which in turn removes the unwanted detail while the important details such as edges are preserved. This technique is advantageous over other simple techniques such linear filtering or smoothing filtering which reduce noise but at the same time smooth away edges to a greater or lesser degree. But, total variation denoising is surprisingly helpful in preserving edges and also smoothing away noise in flat regions. This is applicable even at low signal-to-noise ratios.

B.Multiresolution bilateral filtering

Multi-resolution analysis has is an significant tool for eliminating noises by distinguishing noise from image information. Here signal is decomposed into its frequency sub bands with the help of wavelet decomposition results in the formation of the fine-grain noise from the coarse-grain noise which can also be reconstructed back. These multi-resolution bilateral filter is used for shape and its detailed enhancement from multiple images and also is prospective in eliminating the low-frequency noise components without creating the halo artifacts whereas the standard single-level bilateral filter fails. Bilateral filtering works in estimate sub bands and the application of wavelet thresholding to the detail sub bands, identifies some noise components and remove it effectively. But the problem is, it is not possible to get rid of the coarse-grain noise in higher level.

C.Bishrink Wavelet Algorithm

A wavelet transform is the a function by wavelets. Due to the outstanding localization property of wavelets, has become an obligatory signal and image processing tool for a variety of applications which includes denoising and compression etc..The wavelets are scaled and translated daughter wavelet of a finite-length or fast-decaying oscillating mother wavelet. Conventional Fourier representation find difficult to represent functions that have discontinuities and sharp peaks, and to accurately deconstruct and reconstruct non periodic, finite, and non-stationary signals. Wavelet transforms are classified into discrete wavelet transform and continuous wavelet transforms. Denoising data based on wavelet coefficient thresholding, called wavelet shrinkage. By adaptively thresholding the wavelet coefficient of undesired frequency components denoising operations can be completed.

D.Non-local means Algorithm

For a given discrete noisy image,the estimated value for a pixel for a given noisy image, is computed as a weighted average of all the pixels in the image, where the family of weights depends on the similarity between the neighbouring pixels and these similarity between the neighbouring pixel depends on the similarity of the intensity grey level vectors. This similarity is measurement of the decreasing function of the weighted Euclidean distance. The NL-means compares the grey level in a geometrical configuration in the entire neighbourhood instead of the grey level in single point. This detail allows a more robust comparison than neighbourhood filters.

III. DENOISING FOR 2-D IMAGES

Most of the recent research on image denoising has been focused on methods that reduce noise in transform domain. These transform-based approaches brings good performance in terms of the overall objective but they fall short to preserve details which are not represented by the transform .This often introduce artifacts. The choice of either 2D transform or 3D transform depends on the energy of sparse ability for noise free 2D image blocks and 3D stacked blocks .In sparse 3D collaborative filtering, the given 2D image is grouped into image fragment which is transformed to 3D arrays and dimensional shrinkage is done followed by the reverse 3D transform obtaining the filtered cluster of image blocks is then attenuated from noise by filtering.

In small blocks the neighboring pixels from the natural images show high correlation. Therefore, by establishing decorrelating transforms such as wavelets, DFT, DCT, etc. on those blocks, they can be sparsely represented. The selected unitary transform is able to represent these blocks sparsely. However, the variety of such blocks in natural images often makes the latter assumption satisfied only 2D transform domain and not fulfilled only in 3D transform domain due to the correlation introduced by block matching.

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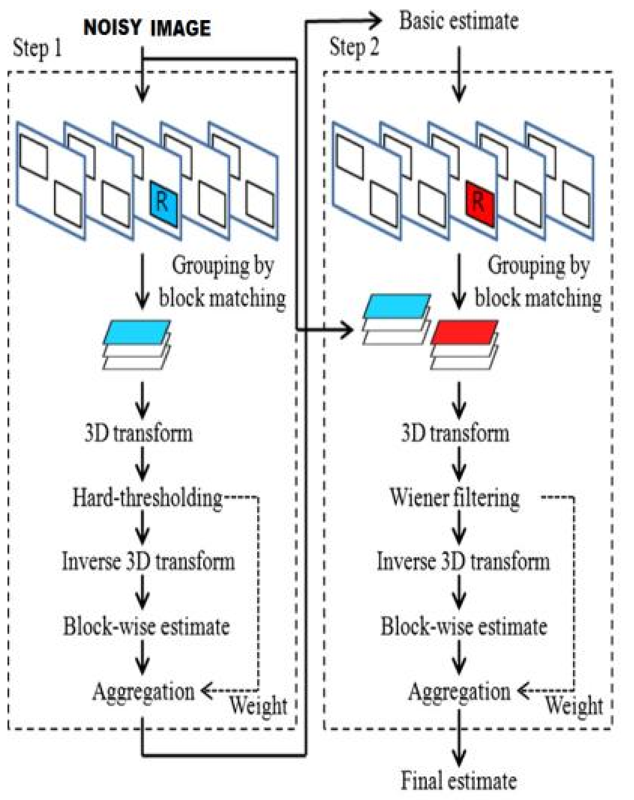

Fig.1.Block Matching Algorithm

The block-matching with 4D transform domain collaborative filtering (BM4D) achieves very good performance in image denoising. However, BM4D becomes ineffective when an image is heavily contaminated by noise. The resulting of poor matching due to the matching out of the region where a template blocks is located. To ignore this, BM3D scheme is given. Efficient noise attenuation is done by applying a shrinkage operator either by hard thresholding or Wiener filtering on the transform coefficients. This helps in improving denoising performance and preservation of the local estimates of the matched blocks, which can be again reconstructed by an inverse 3D transform of the filtered coefficients.

After processing all blocks, the final estimate is obtained by doing weighted average on all overlapping local block-estimates. These overlap will eventually leads to the over completeness of the blocks, resulting in blocking of artifacts and further improvement of the estimated ability. The uniqueness of our enclosed BM3D is two-folded. Firstly, our design BM3D partitions an given image into multiple sub regions, and identifies the boundaries between sub regions. And we restrict block matching search within the region of the template block to avoid deprived matching. Secondly, we do partial block matching for different block coherent segments which belong to different regions in order to avert geometric features such as edges from being removed by collaborative filtering in BM4D.

Compared to BM4D, the proposed bounded BM3D achieves enhanced visual performance, as well PSNR increase for heavily noisy images. We stack the matched noisy to form a 3D array of size , which is denoted by. We apply a unitary 3D transform in order to attain sparse representation of the true signal. The noise is attenuated by hard-thresholding the transform coeffcients. After processing all reference blocks, we have a set of local block estimates , and their corresponding weights which constitute a complete representation of the estimated image due to the overlap between the blocks. It at times few local block estimates might be located at the same coordinate.

A.Algorithm

Step 1: In the noisy image ,find the similar blocks and group them to form a 3d array.
Step 2: Apply hard -thresholding in order to attenuate the high noise levels.
Step 3: Apply inverse 3D transform to obtain estimates.
Step 4: Return the estimates of all the blocks to their original position.
Step 5: Simultaneously ,calculate the estimate of the original image by exploiting the weighted averaging technique.
Step 6: By making use of block matching ,identify the block location which matches the current one and thus form 2 groups both from noisy image and the estimate.
Step 7: Apply collaborative weiner filtering by taking 3D transforms and filtering using energy spectrum followed by inverse 3D transform.

IV. RESULT

BM3D is an algorithm for attenuation of additive white Gaussian noise from grayscale images through which the image denoising is done by sparse 3d transform-domain collaborative filtering. As we know, the performance metrics of the denoising concept is PSNR value. The lower the PSNR value the higher the noise and vice versa. The noisy image taken is a Gaussian noise with the lower PSNR value is denoised by BM3D algorithm achieving a higher PSNR value. This PSNR value yet again increases successively after basic and final estimates. The sparse technique is additionally contributing in space consumption and execution time which is actually demanding in other denoising concepts.

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Fig. 2.Variation of noise levels .(a) Before implementation of bm3d denoising algorithm (PSNR=20.145).(b) After implementation of denoising algorithm (PSNR=29.449).

S.NO	SIGMA VALUE	BASIC ESTIMATE	FINAL ESTIMATE	TIME PERIOD
1	125	20.68 db	21.96db	8.1
2	12	32.90 db	33.11 db	9.0
3	100	22.06 db	23.07 db	7.6
4	150	18.31 db	20.68 db	5.9
5	225	15.55 db	18.34 db	5.7
6	175	16.72 db	19.65 db	7.1
7	250	14.68 db	17.62 db	5.7
8	50	25.47 db	26.04 db	9.0
9	75	23.46 db	24.23 db	9.3
10	25	29.06 db	29.37 db	6.9

V. CONCLUSION

In this paper the powerful Image Denoising is done by Sparse 3D Transform-Domain Collaborative Filtering obtaining a high PSNR value by making use of the BM3D algorithm. It includes basic estimate and final estimate in which each step comprises of the 3D transform, hard thresholding or wiener filtering, their inverse transform, block wise estimate and total aggregation thus gaining high PSNR value.

VI. FUTURE WORK

The future work is to implement this resourceful denoising algorithm to multiple noise sources like salt and pepper, Poisson, etc and to obtain high PSNR values for high level noisy images.

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