

Survey on Image Denoising Algorithms

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Abstract - Natural pictures typically contain patches with high similarity. In this paper, to effectively understand Image noise and its denoising algorithms, we tend to study a ALS algorithm, Higher Order Singular price Decomposition (HOSVD) and Higher order orthogonal iteration (HOOI) for image denoising. Though the low-rank approximation problem has been well studied for matrices, it remains elusive of the on paper extension to tensors due to the NPhard tensor decomposition. In this paper the effective noise removal techniques are discussed for various types of images and the Suggestions for improving the interpretability. The scope of this paper is to give a broad overview of tensors, their decompositions. As part of this, we are going to introduce basic tensor concepts, discuss why tensors can be considered more rigid than matrices with respect to the uniqueness of their decomposition.

Key Words: Image denoising, low-rank approximation, nonlocal similarity, tensor decomposition

1. INTRODUCTION

IMAGE denoising may be a classical inverse downside in natural image process, getting to recover the initial image from a loud image. The essential denoising assumption is that the image has been contaminated with additive white mathematician noise, and therefore the variance of the noise is thought. Mathematically, the strident image Y may be rotten into its original image X and zero-mean statistical distribution noise N,

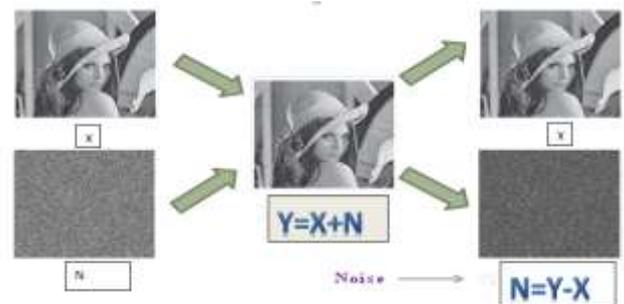
$$Y=X+N$$

To transform the image denoising task into a well-posed Problem, several denoising models are planned by employing varied natural image priors . The classical total variation (TV) models assume that natural pictures satisfy a gradient minimisation constraint that is effective in removing the noise however tends to over-smooth the fine detailed structures. By introducing a redundant illustration, the thin models assume that the clean image content can be effectively delineated by associate degree over-complete wordbook.

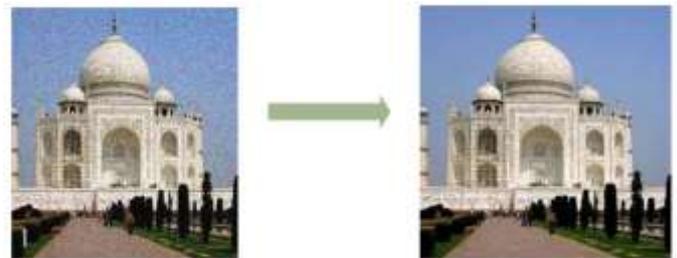
1.1 Image Denoising:

Images captured with digital cameras and traditional film cameras can obtain noise from a spread of sources. Additional use of those pictures can usually need that the noise be (partially) removed – for aesthetic functions as in creative work or selling, or for sensible functions like computer vision. This is the process with which we

reconstruct a signal from a noisy one. So, removing unwanted noise in order to restore the original image or Method of estimating the unknown signal from available noisy data is called as image denoising.



(a) Image Denoising



(b) Image Denoising

Figure 1: Image Denoising

We can say that ultimate goals of image denoising are Remove noise and preserve useful information

1.2 Types of Noise

These are types of noise which are summarized in this paper as below.

1.2.1 Gaussian Noise

Is evenly distributed over the signal .This means that each pixel in the noisy image is the sum of the true pixel value and a random Gaussian distributed noise value

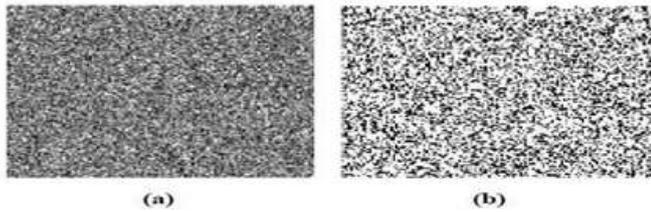


Figure 2: Gaussian Noise

1.2.2 Impulse Noise

The impulse noise is of two types, fixed value and random value. In Fixed value i.e. Salt and pepper noise we can say that It is generally caused due to errors in transmission and It has only two possible values For an 8-bit image, the typical value for pepper noise is 0 and for salt noise 255. In this the corrupted pixels are set alternatively to minimum or to maximum values giving the image Salt and Pepper. While in Random value impulse noise can have any value between 0 and 255 hence its removal is very difficult.

1.2.3 Uniform Noise

The uniform noise cause by quantizing the pixels of image to a number of distinct levels is known as quantization noise. Uniform noise can be analytically described by this image.



Figure 3: Uniform Noise

1.2.4 Periodic Noise

The Source of periodic noise is from electrical or electro-mechanical interference during image acquisition.

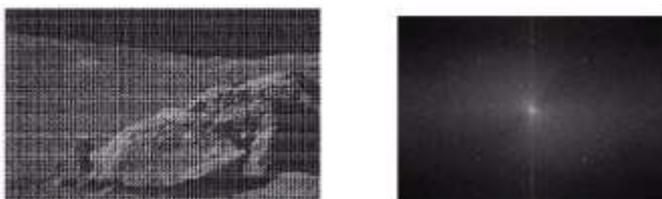


Figure 4: Periodic Noise

1.3 Classification of Denoising Methods

As shown in Figure 5, there are two basic approaches to image denoising, spatial filtering methods and transform domain filtering methods.

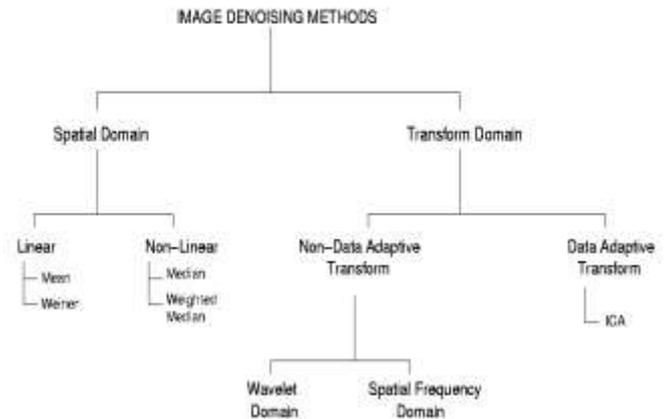


Figure 5: Image Denoising Approaches

1.4 Image Denoising Algorithms

More than a thousand pictures are wont to do the analysis using these CB and pellet filtering techniques to prove that the poor quality pictures are improved terribly efficiently. The filters area unit enhancing look of image and additionally enhance abnormal component values. As way strident pixels have less impact on encircled sensible ones [5], the relation between sensible pixels and strident pixels area unit represented. CB and pellet filters manufacture glorious EME (Quality live of Image Enhancement), MSE, RMSE and PSNR values compared to average filters. CB algorithms scans all neighboring components from center pixel for odd $N \times N$ Matrix. BB filter assigns left corner component rather than center component and so the scanning starts from the left corner component itself.

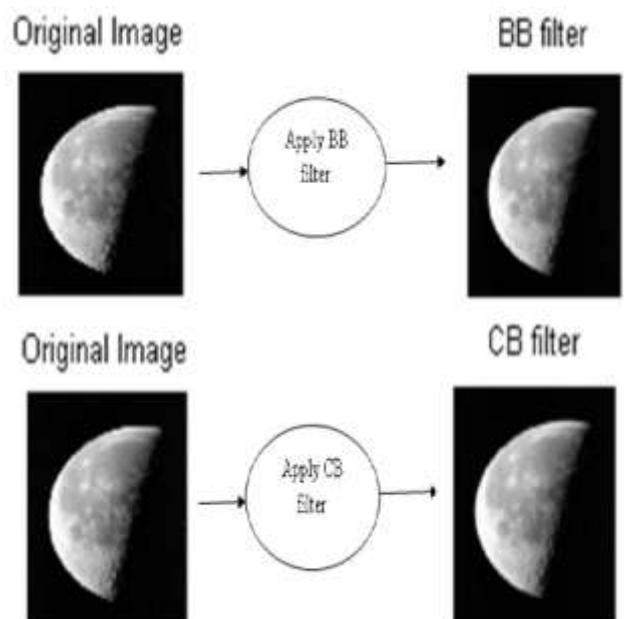


Figure 6: BB and CB Filter

1.4.1. Comparison between CB filter and BB Filter

Table -1: Comparison Table

Sl. No	Parameter	CB Filter	BB Filter	Average Filter
1.	EME	13.06	12.30	12.40
2.	MSE	0.188	0.336	5.855
3.	RMSE	0.434	0.579	2.419
4.	PSNR	55.38	52.86	40.45

1.5 Introduction to Tensors

1.5.1. Tensors

Tensors will be thought of as multi-way collections of numbers, which generally return from a field (like R). In the simplest high-dimensional case, such a tensor would be a three-dimensional array, which may be thought of as an information cube. Throughout this paper, we'll typically seek advice from a three dimensional tensor for motivation and ease. In most cases, the notation naturally extends to higher-dimensional tensors. As we have a tendency to introduce different ideas during this and also the next sections, we'll borrow most of our notation from the excellent review.

1.5.2. Tensor Order

The order of a tensor is that the variety of its dimensions. Scalars will thus be taken as zeroth-order tensors, vectors as first-order tensors, and matrices as second-order tensors. We are going to consult with tensors of order 3 or higher as higher order tensors. Notation-wise, scalars are denoted by graphic symbol letters $x \in \mathbb{R}$, vectors by graphic symbol letters $X \in \mathbb{R}^{I_1 \times I_2}$, matrices by capital letter $X \in \mathbb{R}^{I_1 \times I_2}$, and higher order tensors by Euler script letters $\mathcal{X} \in \mathbb{R}^{I_1 \times I_2 \times \dots \times I_N}$. The I_s denote the number of components within the several dimension. Figure 7 shows how can we move from scalars to tensors.

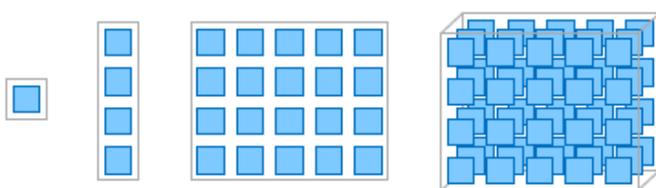


Figure 7: $x \in \mathbb{R}, x \in \mathbb{R}^4, X \in \mathbb{R}^{4 \times 5}, \mathcal{X} \in \mathbb{R}^{4 \times 5 \times 3}$

1.5.3. Tensor Indexing.

We can create subarrays (or subfields) by fixing some of the given tensor's indices. Fibers are created when fixing all but one index, slices (or slabs) are created when fixing all but two indices. For a third order tensor the fibers are given as $x_{:jk} = x_{jk}$ (column), $x_{i:k}$ (row), and $x_{ij:}$ (tube); the slices are given as $X_{::k} = X_k$ (frontal), $X_{:j:}$ (lateral), $X_{i::}$ (horizontal). Graphical examples of fibers and slices for a 3-way tensor are given in Figure 8 and 9.

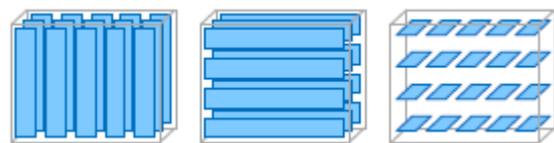


Figure 8: Column, row, and tube fibers of a mode-3 tensor

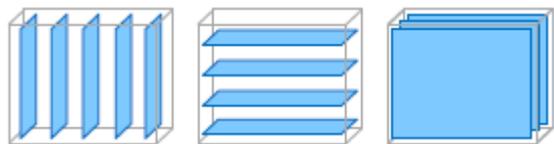


Figure 9: Lateral, horizontal, and frontal slices of a mode-3 Tensor

1.5.4. Outer and real number

The vector outer product is defined because the product of the vector's components. This operation is denoted by the } symbol. The vector outer product of 2 n-sized vectors a, b is defined as follows and produces a matrix $X: X = a \} b = ab^T$

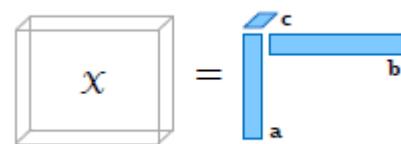


Figure 10: A rank-1 mode-3 tensor

1.6 TENSOR DECOMPOSITION ALGORITHMS

After orientating ourselves with the fundamentals of tensors, we will now address the foremost fashionable tensor decomposition algorithms. While this section can offer a rather theoretical treatment, we also describe the sensible relevancy of tensor decompositions in Section five and Section half dozen. In specific, we have a tendency to square measure curious whether or not we are able to generalize the concept of the SVD from matrices to general tensors. As we will see, there's no single generalization of the SVD thought, but we will discuss 2 decompositions that feature different

generalized properties of the matrix SVD: the canonical polyadic decomposition (CPD) and also the Tucker decomposition. Each square measure outer product decompositions, but they need terribly different structural properties. As a rule of thumb it's sometimes suggested to use CPD for latent parameter estimation and Tucker for mathematical space estimation, compression, and dimensionality reduction. Since CPD and Tucker square measure the foremost vital tensor decomposition and many alternative decompositions square measure supported these 2 techniques.

Algorithm 1 ALS algorithm

```

procedure CP-ALS( $\mathcal{X}, R$ )
  initialize  $A^{(n)} \in R^{I_n \times R}$  for  $n = 1, \dots, N$ 
  repeat
    for  $n = 1, \dots, N$  do
       $V \leftarrow A^{(1)T} A^{(1)} + \dots + A^{(n-1)T} A^{(n-1)} + A^{(n+1)T} A^{(n+1)} + \dots + A^{(N)T} A^{(N)}$ 
       $A^{(n)} \leftarrow X_{(n)} (A^{(N)} \circ \dots \circ A^{(n+1)} \circ A^{(n-1)} \circ \dots \circ A^{(1)}) V^\dagger$ 
      normalize columns of  $A^{(n)}$  (optional)
      store norms as  $\lambda$  (optional)
    end for
  until stopping criterion satisfied
  return  $\lambda, A^{(1)}, \dots, A^{(N)}$ 
end procedure

```

While the ALS algorithmic program printed in algorithmic program one is straightforward to understand and implement, it would take many steps to converge and it would additionally not converge to a worldwide optimum. This implies that the performance of this algorithmic program is influenced by its formatting.

Algorithm 2 HOSVD

```

procedure HOSVD( $\mathcal{X}, R_1, \dots, R_N$ )
  for  $n = 1, \dots, N$  do
     $A^{(n)} \leftarrow R_n$  leading left singular vectors of  $X_{(n)}$ 
  end for
   $\mathcal{G} \leftarrow \mathcal{X} \times_1 A^{(1)T} \times_2 \dots \times_N A^{(N)T}$ 
  return  $\mathcal{G}, A^{(1)}, \dots, A^{(N)}$ 
end procedure

```

Higher Order Singular price Decomposition (HOSVD). We can currently build use of the actual fact that for a given tensor X , we can easily find a definite Tucker decomposition of rank $\langle R_1; R_2; \dots; R_N \rangle$ where $R_n = \text{rank}_n X$. this offers rise to the upper order singular value decomposition (HOSVD). The key plan behind the HOSVD is to find the parts that best capture the variation in mode n , while not considering the opposite modes at now in time [38]. This directly corresponds to the essential PCA thought and may be formalized as seen in Algorithm 2.

Algorithm 3 HOOI

```

procedure HOOI( $\mathcal{X}, R_1, \dots, R_N$ )
  initialize  $A^{(n)} \in R^{I_n \times R}$  for  $n = 1, \dots, N$  using HOSVD
  repeat
    for  $n = 1, \dots, N$  do
       $Y \leftarrow \mathcal{X} \times_1 A^{(1)T} \times_2 \dots \times_{n-1} A^{(n-1)T} \times_{n+1} A^{(n+1)T} \times_{n+2} \dots \times_N A^{(N)T}$ 
       $A^{(n)} \leftarrow R_n$  leading left singular vectors of  $Y_{(n)}$ 
    end for
  until stopping criterion satisfied
   $\mathcal{G} \leftarrow \mathcal{X} \times_1 A^{(1)T} \times_2 \dots \times_N A^{(N)T}$ 
  return  $\mathcal{G}, A^{(1)}, \dots, A^{(N)}$ 
end procedure

```

Higher order orthogonal iteration (HOOI). An alternate Approach to computing the Tucker decomposition is provided by the higher order orthogonal iteration (HOOI). The HOOI is actually an ALS formula that uses the end result of playacting HOSVD on a tensor as a place to begin for initializing the issue matrices [4]. This formula, that is made public in formula three, is particularly advised in cases wherever we tend to solely have access to a truncated HOSVD, since the sequent application of the ALS formula permits for more accurate decompositions.

2. CONCLUSION

We have discussed various denoising algorithms and their performance metrics are compared with individually. The nonlocal means with adaptability shows very good results in image denoising. Though the applications are different, the various denoising schemes perform within their limit. There must be a technique which can be applied globally for all types of noisy images irrespective of the applications. The future research gives the scope for such denoising algorithm which also helps in preserving the necessary sharp details of the image.

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