



A Decomposition Structure for Image Denoising Algorithms

Vinutha Gogineni, C. Raghuvardhan Reddy

Department of Computer Science & Engineering in St.Martin's Engineering College, R.R Dist,
Telangana, India

Abstract: We consider an image decomposition model that provides a novel framework for image denoising. The model computes the components of the image to be processed in a moving frame that encodes its local geometry (directions of gradients and level lines). Then, the strategy we develop is to denoise the components of the image in the moving frame in order to preserve its local geometry, which would have been more affected if processing the image directly. Experiments on a whole image database tested with several denoising methods show that this framework can provide better results than denoising the image directly, both in terms of Peak signal-to-noise ratio and Structural similarity index metrics.

Keywords: Image denoising, differential geometry, local variational method, patch-based method.

I. INTRODUCTION

Denoising is a process of removing noise from a signal. All recording devices, both analog and digital have traits which make them susceptible to noise. Noise can get introduced into the image while capturing or transmission of the image. For this, there have been introduced various linear (such as Weiner filtering) and non linear techniques (such as Thresholding). Thus, the traditional way of image denoising is filtering. But the wavelet transforms have also emerged during the last decade. There are two main types of wavelet transform that is continuous and discrete. Where, the Discrete Wavelet Transformation is now considered more suitable over methods like Fourier and Cosine transforms. Wavelets provide a framework for signal decomposition in the form of a sequence of signals known as approximation signals with decreasing resolution supplemented by a sequence of additional touches called details. Many other methods developed are anisotropic filtering, bilateral filtering, total variation method and non local methods.

Digital images and noise

The need for efficient image restoration methods has grown with the massive production of digital images and movies of all kinds, often taken in poor conditions. No matter how good cameras are, an image improvement is always desirable to extend their range of action. For a sake of simplicity in notation and display of experiments, we shall here be contented with rectangular 2D grey-level images. The two main limitations in image accuracy are categorized as blur and noise. Blur is intrinsic to image acquisition systems, as digital images have a finite number of samples and must satisfy the Shannon-Nyquist sampling conditions. The second main image perturbation is noise.

Signal and noise ratios:

A good quality photograph has about 256 grey level values, where 0 represents black and 255 represents white. Measuring the amount of noise by its standard deviation, $\sigma(n)$, one can define the signal noise ratio (SNR) as

$$SNR = \frac{\sigma(u)}{\sigma(n)}$$

In experimental settings, the noise model is perfectly precise. So the weak point of the algorithms is the inadequacy of the image model. All of the methods assume that the noise is oscillatory, and that the image is smooth, or piecewise smooth.

The "method noise". All denoising methods depend on a filtering parameter h . This parameter measures the degree of filtering applied to the image. For most methods, the parameter h depends on an estimation of the noise variance σ^2 . One can define the result of a denoising method D_h as a decomposition of any image v as

$$v = D_h v + n(D_h, v),$$

where $D_h v$ is more smooth than v and $n(D_h, v)$ is the noise guessed by the method.

II. IMPLEMENTATION

Various techniques for denoising the images based on wavelet transform have been described below.

Universal Thresholding:

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$$T_c = \sigma \sqrt{2 \log M}$$

Differential Geometry:

We first describe the mathematical definition of Riemannian surfaces and several important differential operators, then the discretization of these differential operators are given for triangulated surfaces. In addition, to simplify further computation, sparse matrix representations of these linear operators are given in the end.

Variation Problems and Image Processing on Surfaces:

The variational method in image processing is quite an important approach. After decades of development, many beautiful results are explored, such as variation models of image denoising, image segmentation. However, most results focus on image processing in Euclidean space, in particular, image processing on the 2D plane. With the development of 3D data acquisition technology and the requirement of various applications, there has been increasing interest in studying image processing and variational problems on surfaces or general manifolds. For instance, in fields like computer vision, computer graphics, geometry modeling, medical imaging, computational anatomy, geo-physics and 3D cartoon, it is critical to consider images on 3D surfaces instead of images only on 2D planes.

Numerical Algorithms for Total Variation Related Problems on Surfaces:

To solve the above minimization problems, a direct method could be used is the gradient descent method to find the minimize. However, it has its own limitation of computation speed. As an advantage of the intrinsic method, it is easy to adapt popular fast algorithms to the above total variation related problems on surfaces.

Denoising By Wavelet Thresholding

The wavelet de-noising technique is called thresholding, it is a non linear algorithm. It can be decomposed in tree steps. The first one consists in computing the coefficients of the wavelet transform (WT) which is a linear operation. The second one consists in thresholding these coefficients. The last step is the inversion of the thresholded coefficients by applying the inverse wavelet transform, which leads to the de-noised signal. This technique is simple and efficient. However it relies heavily on the choice of the threshold, which in its turn depends on the noise distribution. In the wavelet thresholding de-noising, we should first select a threshold and process the components of wavelet transform of the noisy signal in order to improve signal-to-noise ratio (SNR).

Soft and Hard thresholding:

There are two types of thresholding techniques applicable to speech processing which are Hard and Soft thresholding. Hard thresholding can be described as the usual process of setting to zero the elements whose absolute values are lower than the threshold. Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards 0.

Implementation steps:

Step:1 Computation of the discrete wavelet transform for noisy speech.

Step:2 Computation of time adaptation factor and multiply with discrete wavelet coefficients using (6).

Step:3 Estimate the noise using (9) and determine the threshold value using (10) then apply different thresholding techniques for the time adaptive wavelet co-efficients using (11), (12) and (13).

Step:4 Inverse Time Adaptive Discrete Wavelet transform is taken through dividing the co-efficients by that adaptation factor, which yields DWT coefficients.

Step:5 Taking Inverse Discrete wavelet Transform (IDWT) the enhanced speech with reduced noise components is obtained while applying trimmed thresholding.

III. CONCLUSION & FEATURE ENHANCEMENT

While the present study is modest in its scope, several interesting but preliminary conclusions do emerge. First, we consider the relative performance of the considered methods. While very popular recently, the NLM method's performance, measured both qualitatively and quantitatively, is inferior to the other two methods. This is a bit surprising given the relatively recent surge of activity in this direction. The computational complexity of the NLM method is also very high, but as we mentioned earlier, this is a problem that has recently been addressed.

A variety of survey has been done in this paper. 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. The limitation of this proposed scheme is the proper tuning of the parameter α for each noise conditions. Future work on this approach will include the adaptation of the parameter α and modified thresholding techniques for other noisy cases like street, helicopter, train noise and industrial noises etc,. Further this algorithm can be implemented in FPGA for enhancing speech in digital hearing aids.

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ABOUT AUTHORS



Mrs. Vinutha Gogineni Post Graduated in Computer Science & Engineering (M. Tech), JNTUH, Hyderabad in 2012 and Graduated in Computer Science & Technology (B. Tech) from JNTU Hyderabad in 2007. She is working as an Assistant Professor in Department of Computer Science & Engineering in **St.Martin's Engineering College**, R.R Dist, Telangana, and Hyderabad. She has 9+ years of Teaching Experience. Her Research Interests Include Computer Networks, Network Security, Big Data, Cloud Computing.



Mr. C. Raghuvardhan Reddy Post Graduated in Computer Science & Engineering (M. Tech), JNTUH in 2015 and Graduated in Computer Science & Engineering (B. Tech) from JNTU Hyderabad in 2013. He is working as an Assistant Professor in Department of Computer Science & Engineering in **St.Martin's Engineering College**, R.RDist, Telangana, and India. He has 1+ years of Teaching Experience. Her Research Interests Include Computer Networks, Network Security.