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Image denoising by preserving geometric components based on weighted bilateral filter and curvelet transform

Sidheswar Routray [a,*], Arun Kumar Ray [a], Chandrabhanu Mishra [b]

[a] School of Electronics Engineering, KIIT University, Bhubaneswar, Odisha, India
[b] Department of Instrumentation and Electronics, CET Bhubaneswar, Odisha, India

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ABSTRACT

Preservation of geometric components during image denoising using weighted bilateral filter and curvelet transforms is explored in this research. The proposed method emphases the texture and artifacts in an image while removing noise efficiently. Restoration of these details in an image not only improves the quality of image but also provides certain intelligence to the user for image understanding. Here, high frequency components are separated through weighted bilateral filter undergo curvelet transforms which leads to retaining of geometric features during the removal of noise components. Based on this, we propose a new method known as WBFCT and tested the performance in a simulated environment. Through a series of simulation of experiments we have compared the denoising performance of WBFCT with Standard Bilateral Filter (SBF), Robust Bilateral Filter (RBF), Weighted Bilateral Filter (WBF), LPG-PCA, KSVD, Curvelet only (Curvelet transform only without taking WBF), Wiener + Curvelet (Wiener filter in place of WBF), WBF + Wavelet (Wavelet transform in place of curvelet transform). Finally, the experimental outcomes divulged that present method has superior performance as compared to existing state-of-the-art methods pertaining to Gaussian noise.

1. Introduction

Image and video communication have become an important part of our everyday life [1]. It is required to capture accurate and clean images for better image understanding and representation. However, modern image capturing devices often introduce noise as noise arises during image acquisition process [2]. The most common type of noise is Additive White Gaussian Noise (AWGN). The mean and variance are same for every pixel and the noise samples are drawn independent of each other in AWGN [3]. The original image $X$is measured in presence of independent additive noise with meanη and standard deviationσ, the measured image can be written as

$$Y = X + \eta \tag{1}$$

In this model, the objective is to restore the original image Xsuch that $Y = X$. Denoising algorithms are used for removing noise from a noisy image while preserving image details such as points, lines, edges and textures [4,5]. Spatial and transformed domain methods have been used to realise the above objective [6]. Transform domain methods are often used due to the superior properties like multi-resolution, sparsity, and edge detection [7]. In transform domain, few coefficients are predominant due to energy compaction. Using shrinkage (hard thresholding) or scaling (soft thresholding) of the transform

* Corresponding author.
E-mail address: sidheswar69@gmail.com (S. Routray).

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coefficients the effects of noise can be suppressed [8]. The denoised image is obtained with help of modified coefficients of the transforms. A variety of such transform-domain methods based on Discrete Cosine Transform (DCT), LPG-PCA [9],Wavelets [10], Curvelets [11], Ridgelets [12], Contourlets [13], Shearlet [31], KSVD [22] etc. are specifically used for image denoising purpose.

Wavelet based transform domain approach is often used for image denoising [9]. In wavelet decomposition, noise and texture details are present in high frequency sub-bands [8]. Therefore, thresholding is used to remove noise. However, the small artifacts (textures) are not properly preserved as affected by thresholding along with noise [9–10].

Candes et al. in [17] introduced a fast curvelet transform which can preserve directional information and also provide near-optimal sparse representation in order to overcome the limitations of wavelet based denoising. Also, Starck et al. in [14] developed an image denoising method called K-Sigma shrinkage based on a recently introduced family of ridgelet and curvelet transforms and it is treated as an alternative to wavelet representation. It provides visually sharper images and also preserves the important edges. However, the shrinkage function considers only individual coefficients but does not depend on inter and intra scale coefficients [14]. Based on strong inter and intra-scale statistical dependencies, Alecu et al. developed a curvelet based method for image processing application [38]. To improve the image denoising performance, Guo et al. used the statistical dependencies between curvelet coefficients and developed an efficient multivariate curvelet based image denoising method [36]. Rabbani et al. in [35] employed a new method which uses three univariate mixture distributions to the image coefficients in sparse domains [35]. The intrascale statistical dependency of the curvelet coefficients are characterized by approximating the parameters of these mixture priors locally. Therefore, curvelet transform helps in retaining the curved edges in an image [28,29]. It is suitable to highlight both line and point characteristics and it is also easy to implement. Therefore, it is preferred over wavelet based image denoising methods [15,16].

In case of curvelet transform, the signal energy is determined in terms of fewer curvelet coefficients. Here, the error of reconstruction which is a function of the largest coefficients decays rapidly and hence, the denoising based on curvelet coefficient thresholding is proved as an efficient technique. Due these advanced properties of curvelet transform, it is used to reduce speckle noise in optical coherence tomography images [34,37].

Another transform domain approach proposed by Do and Vetterli [13] called as Contourlet can deal efficiently with smooth contours. It is directly defined on digital-friendly discrete rectangular grids. However, it has less clear directional geometry than Curvelets so far as artifacts are concerned during image denoising. Recently, a new approach has been introduced for multi-resolution analysis which is called as Shearlet [31]. It forms an affine system with a single shearlet function parameterized by a scaling, a shear, and a translation parameter where, the shear parameter captures the direction of singularities [32]. However, all known constructions of shearlets are band-limited functions with an unbounded support in space domain. In fact, in order to capture the local features of a given image efficiently, representation elements need to be compactly supported in the space domain. It has been shown that both the curvelet and shearlet transforms have the same decay rates [17]. Indeed, using the fast curvelet transform based on transition to Cartesian arrays the discrete implementations of the two transforms are very similar [33].

The potential of the transformed based methods can be exploited by applying them on the texture part of the image. The texture essentially contains the high frequency components. The separation of texture part is obtained through the use of bilateral filtering [18]. Keeping this in view, we combine both spatial domain and the transformed domain in this work. However, the performance of the bilateral filter degrades quickly with increase in noise variance [19–21]. The weighted bilateral filter on the other hand is robust to the noise with large variance [25]. When comparing the transform domain methods, we found apart from the scale and the location parameters, curvelet transform has a unique parameter of the orientation which lets the image analysis up to 72 different angles when the image resolution is 512×512 pixels. Therefore, the preservation of edge and texture of the image is possible with the help of curvelet transform. Therefore, we are motivated to combine weighted bilateral filter and curvelet transform to make use of the advantages of both the approaches.

In this work, we decompose the noisy image into low frequency part and high frequency part using weighted bilateral filter. And then we apply curvelet hard shrinkage to the high-frequency part to preserve the image texture details. During reconstruction, we combine the low-frequency part and the processed high frequency part to get the denoised image. Simulation studies have been carried out in order to test the efficiency of the proposed method with the help of PSNR, VIF and SSIM. Also, we have tested our proposed method by taking different combination of sparse transforms and spatial domain filters in place of WBF and curvelet. We evaluate the denoising performance using curvelet transform only without taking WBF. Also, we have taken wiener filter in place of WBF and reported the results. We substitute wavelet transform in place of curvelet transform and reported the simulation results of the combination of WBF and wavelet. In addition, the result is also compared with some of the existing state-of-the-art image denoising methods. The result shows that there is a substantial improvement in the PSNR, VIF and SSIM measures for the images containing edges.

The rest of the paper is organized as follows. In Section 2.1, we present a short overview of Standard Bilateral filter, Robust Bilateral filter, and Weighted Bilateral Filter and image decomposition using Weighted Bilateral Filter. In Section 2.2, we address the process of edge preservation using Curvelet Transform. We introduce a novel denoising algorithm to preserve the geometric details of an image in Section 2.3. In Section 3, we present the simulation results of the proposed method and compare with some existing methods before concluding the paper in Section 4.