

Survey on Various Image Denoising Techniques

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Abstract - Nowadays digital images are playing an important role in the area of digital image processing. The main challenging factor in image denoising is removal of noise from an image while preserving its details. Noise creates a barrier and it affects the performance by decreasing the resolution, image quality, image visuality and the object recognizing capability in images. Due to noise presence it is difficult for observer to obtain discriminate finer details and real structure of image. One of the main objectives of this survey is to analyse a detailed study in the field of Image denoising techniques.

Key Words: Image Denoising, PSNR, Filtering, Noise Models

1. INTRODUCTION

Any form of signal processing having image as an input & output (or a set of characteristics or parameters of image) is called image processing. In image processing we work in two domains i.e., spatial domain and frequency domain. Spatial domain refers to the digital image plane itself, and image processing method in this category are based on direct manipulation of pixels in an image and coming to frequency domain it is the analysis of mathematical signals or functions with respect to frequency rather than time.

The principal sources of noise in digital images arise during image acquisition and/or transmission. It can be produced by the sensor and circuitry of a digital camera or scanner. Noise degrades the image quality for which there is a need to denoise the image to restore the quality of image. Hence, first question arises is what is noise?. Image noise means unwanted signal. It is random variation of color information and brightness in images, and is usually an aspect of electronic noises. It is an undesirable by-product of image capture that adds spurious and extraneous information. This definition includes everything about a noise.

Many applications are now including the images in their methods, procedures, reports, manuals, data etc., to deal with their clients and image noise is the basic problem with these applications as it affects the data accuracy and efficiency level.

2. LITERATURE SURVEY

In [1] Rizkinia, Tatsuya Baba, Student Member, Keiichiro Shirai, and Masahiro Okuda, proposed a method for local spectral component decomposition based on the line feature of local distribution. It reduce noise on multi-channel images by exploiting the linear correlation in the spectral domain of a local region. First calculate a linear feature over the spectral components of an M -channel image, which call the spectral line, and then, using the line, decompose the image into three components: a single M -channel image and two gray-scale images. By virtue of the decomposition, the noise is concentrated on the two images, and thus LSCD algorithm needs to denoise only the two grayscale images, regardless of the number of the channels. As a result, digital image deterioration due to the imbalance of the spectral component correlation can be avoided.

The experiments show that LSCD improves image quality with less deterioration while preserving vivid contrast. This method is especially effective for hyper spectral images. LSCD method gives higher MPSNR results than those of the other compared methods such as VBM3D [7], PLOW[3], PRI-NL-PCA[4] and Bilateral[5].

In [2], Qiang Guo, Caiming Zhang, Yunfeng Zhang, and Hui Liu, proposed a Efficient SVD- Based Method for Image Denoising. This method first group's image patches by a classification algorithm to achieve many groups of similar patches. The patch grouping step identifies similar image patches by the Euclidean distance based similarity metric. Once the similar patches are identified, and they can be estimated by the low rank approximation in the SVD-based denoising step. In the aggregation step, all processed patches are aggregated to form the denoised image. The back projection step uses the residual image to further improve the denoised result.

Different from other methods such as BM3D[7] and LPG-PCA[4], this method adopts the low rank approximation to estimate digital image patches and uses the back projection to avoid loss of detail information of the image. The computational complexity of this algorithm is lower than most of existing state of the art image denoising algorithms but higher than BM3D. The fixed transform used by BM3D is less complex than SVD, whereas it is less adapted to edges and textures. The main computational cost of algorithm is

the calculation of SVD for each patch group matrix. The MAE value produced by this method is lower than those by other denoising algorithms.

In [3], Priyam Chatterjee, and Peyman Milanfar proposed a Patch-Based Near-Optimal Image Denoising. This framework uses both geometrically and photometrically similar patches to estimate the different filter parameters. Noisy image is first segmented into regions of similar geometric structure. The mean and the covariance of the patches within each cluster are then estimated. Next, for each patch, identify photo metrically similar patches and compute weights based on their similarity to the reference patch. These parameters are then used to perform denoising patch wise. To reduce artefacts, image patches are selected to have some degree of overlap (shared pixels) with their neighbours. A final aggregation step is then used to optimally fuse the multiple estimates for pixels lying on the patch overlaps to form the denoised image.

In terms of visual quality, this method is comparable with LPG-PCA[4] and BM3D[7], even outperforming them in many cases where images exhibit higher levels of redundancy. Compared with PLOW method, SURE-LET [6] takes, on average, 170 s to denoise the same images, whereas the optimized (mex) code for BM3D is much faster (about 1 s). A simple speedup for this method can be achieved by denoising only every third patch, bringing the average execution time down to approximately 17 s. Although this results in a minor drop of 0.2 db in the PSNR, the visual differences are almost imperceptible. BM3D typically does a better job of denoising compared with PLOW [3]

In [4], G M.Vijay Subha.S.V proposed an efficient image restoration technique with the help of Principal Component Analysis (PCA) with local pixel grouping (LPG) and Joint Bilateral Filter (JBF) in spatial domains and it also helps to preserve the image local structures. In LPG-PCA method, a vector variable is modelled by using a pixel and its nearest neighbours and also training sample are extracted using the local window and block matching based LPG. It also helps to preserve image local features after coefficient shrinkage in the PCA domain while eliminating noises. For further improvement, the same procedure is iterated again and the noise level is decreased in the second stage. In the third stage, the LPG-PCA output is used as a reference image for the Joint Bilateral Filter (JBF) to preserve and enhances the edges effectively.

Experimental results shows that LPG gains very competitive denoising performance in terms of PSNR and also the fine structure in an image are preserved .The visual quality shows that this method shows better performance when compare to other methods in reducing various types of noise. Preserved and enhanced the edges effectively. The main drawback is high computational cost due to large number of logic operations like multiplications and additions.

In [5], A. Ravichandran and R. Chaudhr proposed a Image Denoising technique Using Trivariate Shrinkage Filter in the Wavelet Domain and Joint Bilateral Filter in the Spatial Domain. This work presents an efficient algorithm for removing Gaussian noise from corrupted image by incorporating a wavelet-based trivariate shrinkage filter with a spatial-based joint bilateral filter. In the wavelet domain, the wavelet coefficients are modelled as trivariate Gaussian distribution, taking into account the statistical dependencies among intrascale wavelet coefficients, and then a trivariate shrinkage filter is derived by using the maximum a posterior (MAP) estimator.

Wavelet-based methods are efficient in image denoising, when they are prone to producing salient artefacts such as low frequency noise and edge ringing which relate to the structure of the underlying wavelet. Spatial-based algorithms output much higher quality denoising images with less artifacts. However, they are usually too computationally demanding. In order to reduce the computational cost, developed an efficient joint bilateral filter by using the wavelet denoising results rather than directly processing the noisy image in the spatial domain. This filter could suppress the noise while preserve image details with small computational cost.

In [6], Thierry Blu and Florian Luisier proposed new approach to image denoising, based on the image-domain minimization of an estimate of the mean squared error Stein's unbiased risk estimator (SURE). Unlike most existing denoising algorithms, using the SURE makes it needless to hypothesize a statistical model for the noiseless image. A key point of this approach is that, although the nonlinear processing's performed in a transformed domain typically, an undecimated discrete wavelet transform, but also address non orthonormal transforms this minimization is performed in the image domain. Indeed, it demonstrates that, when the transform is a "tight" frame (an undecimated wavelet transform using orthonormal filters), separate subband minimization yields substantially worse results. In order for this approach to be viable, added another principle, that the denoising process can be expressed as a linear combination of elementary denoising processes of linear expansion of thresholds (LET) armed with the SURE and LET principles.

Proposed denoising algorithm merely amounts to solving a linear system of equations which is obviously efficient and fast. Quite remarkably, the very competitive results obtained by performing a simple threshold (image-domain SURE optimized) on the undecimated Haar wavelet coefficients. It shows that the SURE-LET principle has a huge potential. SURE minimization is close to the MSE one, which is an evidence of the robustness of proposed approach. It also simply boils down to solving a linear system of equations, So that algorithm is quite fast compared to BLS-GSM which has the best denoising results. Accordingly, SURE-LET did not try to take advantage of all the degrees of freedom (increased

number of parameters, multivariate thresholding, more sophisticated transforms) to make optimal algorithm.

In [7], Kostadin Dabov,, Alessandro Foi, Vladimir Katkovnik, and Karen egiazarian, proposed a novel image denoising strategy based on an enhanced sparse representation in transform domain. The enhancement of sparsity is achieved by grouping similar 2D fragments of the image into 3D data arrays. It includes three successive steps: 3D transformation of a group, shrinkage of transform spectrum, and inverse 3D transformation. Due to the similarity between the grouped blocks, the transform can achieve a highly sparse representation of the true signal so that the noise can be well separated by shrinkage. In this way, the collaborative filtering reveals even the finest details shared by grouped fragments and at the same time it preserves the essential unique features of each individual fragment.

This approach can be adapted to various noise models such as additive colored noise, non Gaussian noise. The PSNR results highest for denoising additive white Gaussian noise from grayscale and color images. Furthermore, the algorithm achieves these results at reasonable computational cost and allows for effective complexity/performance trade-off.

IMAGE (NOISE LEVEL=10)	LSCD[1]	SVD[2]	PLOW[3]	LPG-PCA[4]	BILATERAL[5]	SURE-LET[6]	BM3D[7]
LENA	36.07	35.48	35.31	35.75	31.25	32.18	34.98
BARBERA	35.10	34.38	33.85	35.07	31.98	32.90	33.92
HILL	33.43	33.82	32.62	33.40	31.94	32.69	33.62
CAMERA MAN	33.25	34.52	32.98	33.68	31.49	33.18	34.68

Table: Comparison of the PSNR (db) results of different denoising methods on test images. The best results are highlighted in bold.

3. CONCLUSIONS

This paper provides an outline of digital image denoising techniques. Denoising image is a long standing problem for many image processing applications. Various systems are effectively and significantly benefit the solution of image recovery problems. Some research papers were discussed, all focussing on different aspects & techniques of image denoising. All algorithms have some pros & cons of their own and this can be gleaned from this review. It could be seen that majority of the works focused on removal of gaussian noise. The noisy images were denoised using several algorithms and the PSNR results were analysed. According to the analysis, LSCD provide better PSNR results. The major role of this paper is to draw a picture of the state of the art of the image denoising techniques.

REFERENCES

- [1] Mia Rizkinia, Tatsuya Baba, Student Member, Keiichiro Shirai, and Masahiro Okuda, "Local Spectral Component Decomposition for Multi-Channel Image Denoising," in IEEE Transactions on Image Processing, vol.25, NO. 7, July 2016 .
- [2] Qiang Guo, Caiming Zhang, Yunfeng Zhang, and Hui Liu, "An Efficient SVD- Based Method for Image Denoising," IEEE Trans. Video Technology, vol. 51, no. 2, pp. 91-109, 2015
- [3] Priyam Chatterjee, Student Member, IEEE, and Peyman Milanfar, Fellow, IEEE, "Patch-Based Near-Optimal Image Denoising," IEEE Trans. Image Processing, OL. 21, NO. 4, APRIL 2012.
- [4] GM.Vijay Subha.S.V, "Spatially Adaptive Image Restoration Method Using LPG-PCA And JBF ", IEEE Int. Conf. On Image Processing, Mar. 2012.
- [5] A. Ravichandran, R. Chaudhry and R. Vidal, "Image Denoising Using Trivariate Shrinkage Filter in the Wavelet Domain and Joint Bilateral Filter in the Spatial Domain," vol. 35, no. 2, pp. 342-353, October 2009.
- [6] Thierry Blu, Senior Member, IEEE, and Florian Luisier, "The SURE-LET Approach to Image Denoising", IEEE Transactions On Image Processing, Vol. 16, No. 11, November 2007
- [7]] Kostadin Dabov,, Alessandro Foi, Vladimir Katkovnik, and Karen egiazarian, "Denoising by Sparse 3-D Transform-Domain Collaborative Filtering "IEEE Transactions on Image Processing, vol. 12, no. 11 pp. 1338-1351, November 2005