ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

IJESRT

INTERNATIONAL JOURNAL OF ENGINEERING SCIENCES & RESEARCH TECHNOLOGY

A SURVEY ON NOISE REDUCTION TECHNIQUE BASED ON DIFFERENT NOISES

Nagarjunan D*, Gracy Theresa.W
*PG Scholar Dept of CSE, Adhiyamaan college of engineering, Hosur, Krishnagiri, India,
Assistant Professor Dept of CSE, Adhiyamaan college of engineering, Hosur, Krishnagiri, India

ABSTRACT

Removal of Noise in the image is challenging task in Image processing. Now-a-days there are so many methods that are available to remove noise from digital images. This introduced noise by image enhancement methods, in particular algorithms based on the random spray sampling technique, but not only. According to the nature of sprays, output images of spray-based methods tend to exhibit noise with unknown statistical distribution. Most of the novel method comprises two stages: the first stage is to detect the noise in the image. At this stage, based on the intensity values, the pixels are roughly divided into "noise-free pixel" and "noisy pixel". Then, the second stage is to eliminate the noise from the image. At this stage, only the "noise-pixels" are processed. Some methods proposed to remove noise in the Image based on Contourlet-Domain HMT Models Using Cycle Spinning, Spatio-Temporal Retinex inspired Envelope with Stochastic Sampling (STRESS) used in gray scale images, steerable pyramid domain based on a local Laplace prior, Dual-tree Complex Wavelet Transform based denoising for Random Spray image enhancement methods, Adaptive Shrinkage for Image Denoising Based on Contourlet Transform. But these are some disadvantages in them.

KEYWORDS:

INTRODUCTION

Although the field of image enhancement has been active since before digital imagery achieved a consumer status, it has never stopped evolving. The present work introduces a novel multi-resolution denoising method, tailored to address a specific image quality problem that arises when using image enhancement algorithms based on random spray sampling. While inspired by the peculiar problem of such methods, the proposed approach also works for other image enhancement methods that either introduce or exacerbate noise.
Denoising Methods

Contourlet-Domain HMT Models Using Cycle Spinning

The approach to image denoising based on CHMT. Here utilized the cycle spinning algorithm in developing a translation invariant CHMT denoising scheme. Here they provide the noisy image, which will be convert as a signal by contourlet transform, then they apply the circular shifting. Then apply the EM training for denoising. The experiment results clearly demonstrated the capability of the proposed scheme in image denoising experiments. This scheme achieves enhanced estimation results for noisy images. This approach outperforms the CHMT-based denoising method [3].

Spatio-Temporal Retinex inspired Envelope with Stochastic Sampling (STRESS)

This method presented a new framework for spatially re-computing the color of a digital image. The color of each pixel is recomputed by scaling its channel lightness value according to two upper and lower envelope functions. These envelope functions are obtained sampling a limited number of pixels in the neighbor. The algorithm performs local color and lightness adjustments in an edge-preserving manner by means of spatial comparisons [4].

Speckle Suppression for SAR Images Based on Adaptive Shrinkage in Contourlet Domain

This paper presented a novel contourlet-based speckle suppression algorithm for SAR images [6]. Firstly, logarithmic transform is used to convert the multiplicative speckle mode into an additional white Gaussian noise model. Hard thresholding algorithm and cycle spinning technique are utilized in contourlet domain. For the property of speckle noise is already known, the standard deviation of speckle noise is estimated by the Monte-Carlo simulation. Experimental results demonstrate that our algorithm has good speckle suppression performance and typically preserves more texture and details. In future work, we plan to further improve the performance of this speckle suppression algorithm by combing some other techniques, such as Bayesian model and Hidden Markov Tree Model (HMT)

Adaptive Shrinkage for Image Denoising Based on Contourlet Transform

This presents a new local adaptive shrinkage threshold for image denoising based on contourlet transform [5]. Unlike classical shrinkage threshold, the new shrinkage threshold takes account of the image characteristics. The noise level, the scale of the contourlet coefficients, and the neighbourhood window around the contourlet coefficients to be thresholded jointly define the proposed shrinkage threshold. This adaptive shrinkage threshold leads to efficient and adaptive methods for image denoising, such as LAS and LAS-CS. The methods are simple, both conceptually and computationally. The numerical results clearly demonstrated that using the proposed shrinkage threshold, we can obtain better denoising results, in terms of both PSNR values and visual quality, especially for the images that include plentiful textures and edges

Image denoising in steerable pyramid domain based on a local Laplace prior

This method use SoftLMAP and SoftLMMSE functions based on Laplace pdf with local variance for modeling of steerable pyramid coefficients [7]. Experiments show our spatially adaptive algorithm has better results than other methods such as BLS-GSM. There are two important factor for denoising in sparse domain i.e., the proposed transform and the obtained estimator. It seems that denoising in steerable pyramid (instead of other transforms such as wavelet) domain plays a key role to improvement the results. However, as BLS-GSM also is based on the steerable pyramid but with a more complex priori model, we can conclude that the simple proposed priori distribution in this paper is the primary reason for improvement. In fact, for the proposed images in this paper, the local Laplace pdf is more appropriate model for image modeling in steerable pyramid decomposition.

Foveated self-similarity in nonlocal image ltering

The Foveated NL-means [8] algorithm performs comparably to the standard NL-means whenever there are plenty of mutually similar patches, such as in areas with smooth or periodic content. This allowed us to avoid any customized tuning of the foveated algorithm, and just utilize the parameters that work well for the NL-means.

Dual-tree Complex Wavelet Transform based denoising for Random Spray image enahcement methods

This method approaches the problem via wavelet coefficient shrinkage. Algorithms based on wavelet shrinkage have a long history, nonetheless this work presents a novel view on the subject. This article was particularly inspired by the works on the Dual-tree Complex Wavelet Transform [1], the work on the Steerable Pyramid Transform by Simoncelli et al., and the work on Wavelet Coefficient Shrinkage by Donoho and Johnstone.

NOISE AND DENOISING METHODOLOGY

Contourlet-Domain HMT Models Using Cycle Spinning

The contourlet coefficients are nonGaussian but conditionally Gaussian which can be accurately modeled by mixtures of Gaussian distributions whose variances depend on their generalized neighborhood coefficients. Conditioned on the magnitudes of their generalized neighborhood coefficients, contourlet coefficients are zero-mean Gaussian distributed. The parent coefficient is typically the most significant predictor when generalized neighborhood coefficients are considered individually. Contourlet coefficients are similar to wavelet coefficients and the persistence and clustering are obvious, So Duncan D.Y. Po generalized WHMT model to contourlet and constructed a CHMT model.

Compared with WHMT, the CHMT model has a major advantage that it accounts for interdirection dependencies while WHMT does not. In the WHMT model, the parent- children links are always in the same direction among three wavelet directions. As a result, the coefficients of three directional subbands in WHMT are independent. In contrast, contourlet coefficients can have their four children in two separate directional subbands. The dependence tree in the CHMT can span several adjacent directions in the finer scales, and thus, interdirection dependencies are modeled in a similar way as interlocation dependencies. In other words, the CHMT can effectively capture all dependencies across scales, space, and directions.

Cycle spinning for denoising is a simple yet efficient method that can be applied to a shift variant transform for signal and image denoising. Since contourlet transform is a shift variant transform, we use cycle spinning to enhance CHMT-baseddenoising results.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Denote the 2-D circular shift by CS x, y and the CHMT-based denoising operator by CHMTD, the proposed denoising method can be written as

$$\hat{s} = \frac{1}{K_1 K_2} \sum_{x=1,y=1}^{K_1,K_2} CS_{-x,-y}\left(CHMTD\left(CS_{x,y}\left(sn\right)\right)\right)$$

where (K1, K2) are the maximum number of shifts, sn is the noisy image, sˆ is the estimation of the clean image.

Spatio-Temporal Retinex inspired Envelope with Stochastic Sampling (STRESS)

For each pixel, p0, the values of the maximum and mini- mum envelopes, Emax and Emin at the corresponding positions, are computed in an iterative manner using N iterations. In every iteration, M pixels intensity values pj ; i 2 f1; …; Mg, are sampled at random with a probabil- ity proportional to 1=d, d being the Euclidean distance in the image from the sampled pixel to the pixel in question. The intensity value of the center pixel, p0, is not eligible for random sampling but is always included in the sampled set. The pixels are sampled only from a disk with radius R around the center pixel. When using such a random spray to sample the image, the strategy we have chosen when a sample outside the image is attempted is simply to try again until a sample within the image is found. From these samples, the maximum and minimum samples in the spray are found:

$$s_i^{\max} = \max_{j \in \{0,\ldots,M\}} p_j,$$

$$s_i^{\min} = \min_{j \in \{0,\ldots,M\}} p_j.$$

Since P_0 is always one of the sample points, $s_i^{\max} \leq p_0 \leq s_i^{\max}$ always.

Speckle Suppression for SAR Images Based on Adaptive Shrinkage in Contourlet Domain

For the ability of working under all weather conditions, synthetic aperture radar (SAR) is a highly effective instrument for gathering information from earth’s surface. It can obtain remotely sensed images of high resolution, and is well suited to various tasks such as glaciology, agriculture, oceanography, forestry and many military applications. However, due to coherent interference of backscattered electromagnetic signals, SAR images are usually contaminated by severe speckle noises. Speckle noise reduces the resolution of SAR images and will bring degradation in the content, thus making subsequent analysis, classifications and recognition more difficult. So far, numerous speckle reduction algorithms for SAR images have been developed. These algorithms can be classified into two categories: (1) Algorithms based on digital signal filter, including the Lee filter, the Forest filter, the Gamma filter and the MAP filter. These standard filters usually perform well in speckle reduction; but they also have fatal limitations in preserving sharp features of the original image and high computational complexity. (2) Algorithms based on wavelets. Wavelet is a powerful denoising tool for its properties of good localization in both spatial and spectrum domains, good separation of noise and signal contents, flexibility of different resolutions. However, wavelet-based methods usually cause severe visual artifacts like the ringing effect and Gibbs effect, and are still difficult to preserve original edges and discontinuities, which is extremely important in SAR image processing. This present a new speckle suppression algorithm based on adaptive shrinkage in contourlet domain. Contourlet is a "true" two dimensional sparse representation tool for images, and has been proved to be more suitable for image processing than wavelet. The basic idea of the proposed despeckling algorithm is to suppress speckle noise by adaptively reducing the significant high-frequency contourlet coefficients while releasing the low-frequency contourlet and small coefficients. Logarithmic transform, Monte-Carlo simulation and cycle spinning technique are utilized to improve performance of speckle reduction.

Wavelet is an optimal tool for 1-D piecewise smooth signals, however, it has serious limitations in dealing with high dimensional signals. In natural images, discontinuity points are typically positioned along smooth edges. However, as a tense-product of 1-D wavelet, wavelet in two dimensions is only good at isolating the discontinuities at edge points, but can not detect the smoothness along the edges. On the other hand, 2-D separable wavelet decomposes image in only three directional subbands, namely, vertical, horizontal and diagonal. So wavelet can only capture limited directional information.

Adaptive Shrinkage for Image Denoising Based on Contourlet Transform

The contourlet coefficients are correlated to adjacent coefficients as wavelet coefficients, which can be called the clustering property [8]. A large contourlet coefficient, which tends to contain information of

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

important singularity, will probably have large coefficients as its neighbours.

In this section, we present a new local adaptive shrinkage threshold function based on the mean filtering of the absolute values of the contourlet coefficients. The proposed shrinkage threshold function can be expressed as:

$$T(s,d,m,n)=\left(\lambda-e^{\frac{(E(s,d)-M(s,d))\log(\lambda-1)}{A(s,d,m,n)-M(s,d)}}\right)k\hat{\sigma}_{s,d}\sigma$$

where A(s,d,m,n)are generated by a mean filter on the absolute values of contourlet coefficients:

$$A(s,d,m,n)=\frac{1}{N}\sum_{(m,n)\in B}\left|C(s,d,m,n)\right|$$

where B is the neighbourhood square window of the contourlet coefficient C(s,d,m,n) , and we chose 3×3 window in our experiments. N number in the B . The coefficients at the boundary of the contourlet domain are processed with the odd symmetric extension method.

E(s,d) denotes the mean values of the functionA(s,d,m,n), and M(s,d) denotes the minimum values ofA(s,d,m,n) . λ is a constant that satisfies the condition $1< \lambda< 2$, and we choose λ=1.06 in latter experiments.

Comparing the proposed shrinkage threshold with the classical shrinkage threshold highlights the improvement of the new shrinkage threshold. Figure 2 shows the proposed local adaptive shrinkage threshold against the function A(s,d,m,n) for a subband indexed by scale s and direction d .

As seen, compared with the classical shrinkage threshold, the shrinkage threshold proposed considers the characteristics of the neighbouring contourlet coefficients. The new threshold preserves more significant coefficients that contain information of important singularity, and at the same time, attenuates more coefficients with small neighbouring mean values, which contain information of noise. So the proposed threshold should obtain better denoising results.

Image denoising in steerable pyramid domain based on a local Laplace prior

The main contribution of this paper is using local Laplace prior for statistical modeling of steerable pyramid coefficients and employing this prior for MAP and MMSE estimation of noisy data. In this base, we assume that kth component of input image x = [x1, ... ,xl] (l is the number of pixels in image) is corrupted by AWGN k of zero-mean and standard deviation n. We observe a noisy signal gk = xk+ k for k = 1, ... ,land wish to estimate the noise-free signal xk as accurately as possible according to some criteria such as MAP or MMSE. For lin- ear transforms such as steerable pyramid, the noise remains additive in the transform domain as well. Thus we can write yk = wk+nk for k = 1, ... ,l, where yk is the noisy coefficient, wk is the noise-free co- efficient and nkis independent, identically distributed (i.i.d.) normal random variablesnk~N(0, n).

The Laplace priors are well-known in the literature and have been widely used in the case of wavelets . This simple distribution is able to model the heavy-tailed nature of wavelets. On the other hand, many researchers propose a local Wiener filter (that is based on Gaussian prior) to remove the noise according to the local statistics of the images. In this paper, to benefit from the advantages of both mentioned approaches, we model the coefficients of steerable pyramid as a realization of a doubly stochastic process. Specifically, the coefficients are assumed to be condition- ally independent zero-mean Laplacian random variables, given their variances. These variances are modeled as highly correlated random variables. Indeed, we model the coefficients as conditionally independent Laplacian random variables rather than Laplace variables. This model is able to capture the heavy-tailed nature of marginal pdf and dependency between spatial adjacent in each subband. These properties were explained in the literature review section, and in the following we evaluate the ability of proposed local Laplace pdf for statistical modeling of steerable pyramid decomposition.

Foveated self-similarity in nonlocal image ltering

The superior sharpness and contrast achieved by the Foveated NL-means come perhaps unexpected, because the foveated self-similarity is assessed on blurred data. This paradox is however only apparent, because in the weighted averaging what matters is that w (x1; x2) is small when jy(x1) y(x2)j is large, and vice versa. The quality improvement achieved using foveation suggests that the similarity between the noise-free central pixels correlates better with the foveated patch similarity than with the windowed similarity. This should not surprise, since foveation suppresses high-frequency components at the periphery of the patch, and these components are typically less correlated with those at center of the patch than the low-frequency components are. While

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

a direct parallel may not be obvious, it is nevertheless interesting to observe that also in the HVS foveation plays indeed a role in increasing the dynamic range and the signal-to-noise ratio at low-light conditions, at the expense of blurring the peripheral perception. In particular, we conjecture that some form of foveatedself-similarity may be relevant in trans-saccadic integration (e.g.,21), a process that vaguely reminds of the Foveated NL-means.

In terms of computational complexity, the foveated distance can be introduced at negligible computational cost, because the foveation operator \ requires only the preliminary computation of the jKj convolutions of zagainst the blurring kernels v&(i); i 2 K. Note that the cardinality of K is often much smaller than the number jUjof pixels in the patch (e.g., in our experiments jKj=5 and jUj=121).

Finally, we wish to remark that, in spite of the substantial improvement achieved by introducing foveation inNL-means, the performance of these algorithms is still inferior to that of more sophisticated nonlocal …lters, such as, e.g., BM3D5 or SAFIR.6 As a …gure of merit, BM3D achieves a PSNR of 31.26 dB when denoising Lena corrupted by noise with = 30, versus 29.23 dB of NL-means and 30.53 dB of Foveated NL-means.However, our contribution is not to be intended as the development of yet another denoising algorithm, but rather as the exploration of a new form of nonlocal self-similarity.

Dual-tree Complex Wavelet Transform based denoising for Random Spray image enahcement methods

Kingsbury developed the Complex Wavelet Transform (CWT) in order to solve certain problems that arise with the traditional Discrete Wavelet Transform (DWT), as well as other more advanced methods such as the Steerable Pyramid Trans- form (SPT). Similarly to the SPT, in order to retain the whole Fourier spectrum, the CWT needs to be overcomplete by a factor 4, i.e. there are 3 complex coefficients for each real one. The CWT is also efficient, as it can be computed through separable filters, yet it lacks the Perfect Reconstruction property. Kingsbury also introduced the concept of Dual-tree Com- plex Wavelet Transform (DTCWT), which has the added charac- teristic of Perfect Reconstruction at the cost of only approximateshift-invariance.

Since the a full discussion on the Dual-Tree Complex Wavelet Transform would be too cumbersome, only a brief in- troduction the 2D variant of the DTCWT is given [1]. The reader is referred to the the work by Selesnick et al. for a very comprehensive coverage on the DTCWT and the relationship it shares with other transforms.

The 2D Dual Tree Complex Wavelet Transform can be im- plemented by using two distinct sets of separable 2D wavelet bases, as shown below.

$$\psi_{1,1}(x,y) = \phi_h(x)\psi_h(y), \quad \psi_{2,1}(x,y) = \phi_g(x)\psi_g(y),$$
$$\psi_{1,2}(x,y) = \psi_h(x)\phi_h(y), \quad \psi_{2,2}(x,y) = \psi_g(x)\phi_g(y),$$
$$\psi_{1,3}(x,y) = \psi_h(x)\psi_h(y) \quad \psi_{2,3}(x,y) = \psi_g(x)\psi_g(y)$$

$$\psi_{3,1}(x,y) = \phi_g(x)\psi_h(y), \quad \psi_{4,1}(x,y) = \phi_h(x)\psi_g(y),$$
$$\psi_{3,2}(x,y) = \psi_g(x)\phi_h(y), \quad \psi_{4,2}(x,y) = \psi_h(x)\phi_g(y),$$
$$\psi_{3,3}(x,y) = \psi_g(x)\psi_h(y) \quad \psi_{4,3}(x,y) = \psi_h(x)\psi_g(y)$$

The following equations shows the relationship between wavelet filters h and g

$$g_0(n) \approx h_0(n-1), \text{ for } j = 1$$
$$g_0(n) \approx h_0(n-0.5), \text{ for } j > 1$$

where j is the decomposition level.

When combined, the bases give rise to two sets of real , two dimensional , oriented wavelets

$$\psi_i(x,y) = \frac{1}{\sqrt{2}}\left(\psi_{1,i}(x,y) - \psi_{2,i}(x,y)\right)$$

$$\psi_i + 3(x,y) = \frac{1}{\sqrt{2}}\left(\psi_{1,i}(x,y) + \psi_{2,i}(x,y)\right)$$

$$\psi_i + 3(x,y) = \frac{1}{\sqrt{2}}\left(\psi_{3,i}(x,y) - \psi_{4,i}(x,y)\right)$$

The most interesting characteristic of such wavelets is that they are approximately Hilbert pairs. One can thus interpret the coefficients deriving from one tree as imaginary, and obtain the desired 2D DTCWT

CONCLUSION

In order to achieve noise reduction, the proposed method leverages the data orientation discriminating power of the Dual Tree Complex Wavelet Transform, as well as the information contained in the non-enhanced image. Wavelet coefficient shrinkage and selection are the basic mechanisms underlying the iterative processing. Unlike most of the state of the art, this approach requires no prior knowledge of the statistical properties of noise. The only parameter that the user is required to choose explicitly is the depth of the DTCWT.

ISSN: 2277-9655
Scientific Journal Impact Factor: 3.449
(ISRA), Impact Factor: 2.114

Performance has been tested in two ways. First, noise with different statistical properties has been added to images with a well known reference. The proposed approach was able to achieve great improvements in both PSNRs and SSIM scores in- dependently of the noise distribution.
The proposed approach has then been compared to a recent development of the NL-means denoising algorithm, using im- ages with a well known prior contaminated by Gaussian noise of varying standard deviation. Our method shows consistent in- creases in PSNR of about 9 dBs on average, as well as higher SSIM scores, never dropping below 0.85.
The proposed noise reduction approach shows great ability in removing noise without altering the underlying structures, al- though its performance is naturally limited by the contrast of thenon-enhanced image.

REFERENCES

1. Fierro, M, Kyung, W.-J & Ha, Y.-H 2012, ‘Dual-tree complex wavelet transform based denoising for random spray image enhancement methods’, in Proc. 6th Eur. Conf. Color Graph., Imag. Vis.,,pp. 194–199.
2. Foucher, S, Farage, G & Benie, G 2006, ‘Sar image filtering based on the stationary contourlet transform’, in Proc. IEEE Int. Geosci. RemoteSens. Symp., pp. 4021–4024
3. Kang Li, Wei Wang, & Jinghuai Gao 2008, ‘Image Denoising Based on Contourlet-Domain HMT Models Using Cycle Spinning’, CSSE 6, page 162-165. IEEE Computer Society.
4. Kolås, Ø, Farup, I & Rizzi, A 2011, ‘Spatio-temporal retinex-inspired envelope with stochastic sampling: A framework for spatial color algorithms’, J. Imag. Sci. Technol., vol. 55, no. 4, pp. 1–10.
5. Li, K, Gao, J & Wang, W 2008, ‘Adaptive shrinkage for image denoising based on contourlet transform’, in Proc. 2nd Int. Symp. Intell. Inf.Technol. Appl., vol. 2., pp. 995–999.
6. Ni, W, Guo, B, Yan, Y & Yang, L 2006, ‘Speckle suppression for sar images based on adaptive shrinkage in contourlet domain’, in Proc. 8th World Congr. Intell. Control Autom., vol. 2, pp. 10017–10021.
7. Rabbani, H 2009, ‘Image denoising in steerable pyramid domain based on a local laplace prior’, Pattern Recognit., vol. 42, no. 9, pp. 2181–2193.
8. A. Foi and G. Boracchi, “Foveated self-similarity in nonlocal image filtering,” Proc. SPIE, vol. 8291, p. 829110, Jan. 2012.