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An Efficient Image Denoising Method using SVM Classification

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***Abstract*— Image denoising algorithms usually are dependent on the type of noise present in the image. There is a great need of a more generally usable, noise independent denoising algorithm. In this paper, an image denoising technique is proposed where the image is first transformed to the nonsubsampled contourlet transform (NSCT) domain, detail coefficients are extracted and feature vector for a pixel in the noisy image is formed by the spatial regularity. The support vector machine (SVM) is then used for classifying noisy pixels from the edge related ones. Finally, the denoising is done by shrink method, where an adaptive Bayesian threshold is utilized to remove noise. Experimental results show that the method gives good performance in terms of visual quality as well as the objective metrics such as peak signal to noise ratio (PSNR).**

***Keywords:* Image denoising; Non subsampled contourlet transform; Support Vector Machine classifier**

I. INTRODUCTION

The main challenge for image denoising is to preserve the information bearing structures such as edges and textures to get satisfactory visual quality while improving signal to noise ratio (SNR). Initially conventional techniques of spatial and transform domain filtering were used for denoising, which includes mean filter, median filter, order statistics filter, adaptive filters etc. Image denoising based on total variation [Rudin et al.(1992)], anisotropic diffusion [Gerig (1992)], bilateral filtering [Tomasi et al.(1998)], mixture models [Portilla et al.(2003)] and non-local means [Brox et al.(2008)] widely emerged as improvisations for noisy images. However, these methods either exhibited certain disturbing artifacts or were efficient only for particular kinds of noise.

The field of image denoising realised a boom in performance with the use of wavelets [Lusier et al.(2007)]. Wavelets in 2-D are good at isolating the discontinuities at edge points, but will not "see" the smoothness along the contours. In addition, separable wavelets can capture only limited directional information [Do et al.(2005)]. This led to the rise of directional, redundant, shift variant transforms such as contourlet transform.

In applications such as denoising, enhancement and contour detection, a redundant representation can significantly outperform a non-redundant one. Subsequently, the shift invariant and non-redundant transform called the non-subsampled contourlet transform (NSCT) was designed [Cunha et al. (2006)]. More importantly, it provides the spatial relationship between pixels in the original image by a few, large, spatially contiguous coefficients in the NSCT domain, which represent features of the image and should be retained as much as possible during denoising.

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The use of Support Vector Machine (SVM) for denoising has evolved recently. SVM based classifier is built to minimize the structural misclassification risk, where as conventional classification techniques often apply minimization of empirical risk [Cheng et al. (2004)]. Therefore, SVM is claimed to lead enhanced generalization properties. Further, application of SVM results in global solution for a classification problem. In the proposed method, SVM is used to classify the noisy NSCT coefficients from the non-noisy ones.

II. Proposed Method

The proposed method works well for both gray scale images as well as colour images. The process flow is as explained below:

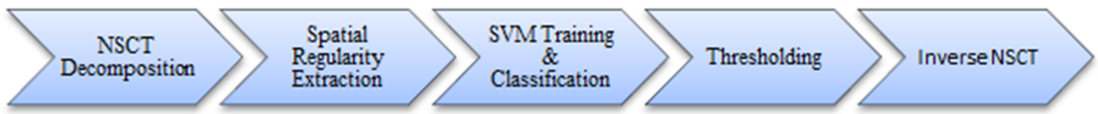


Figure 1: Process flow of the proposed method

A. NSCT decomposition

Perform a J level NSCT decomposition on the noisy image, and obtain a low-pass subband $A_1$and a series of high-pass subbands D_k^s (k = 1, 2,…. J; s = 1, 2,….H). Here, k denotes the decomposition level, and s denotes the decomposition orientation, H is the maximum number of decomposition direction.

B. Binary map

Form a preliminary binary label for each NSCT coefficient, which collectively form a binary map. The NSCT of noisy image generates NSCT coefficients C(x,y) which is used to create the preliminary binary map I(x,y).

$$I(x,y) = \begin{cases} 1, & |C(x,y)| > \tau \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where τ is the threshold for selecting valid coefficients in the construction of the binary NSCT coefficient map. τ is a threshold calculated from the Otsu thresholding, thereby the thresholding depends on the between class variance of the image, rather than noise variance.

C. Spatial Regularity Extraction

Because of the spatial regularity, the resulting NSCT subbands generally do not contain isolated coefficients. Spatial regularity in the preliminary binary map is used to further examine the role of the valid NSCT coefficient; whether it is isolated noise or part of a spatial feature. The number of supporting binary values around a particular nonzero value I(x,y) is used to make the judgement. The support value is the sum of all I(x,y) which support the current binary value, ie. The total number of all valid NSCT coefficients which are spatially connected to the current I(x,y).

D. Feature vector formation

For each subband D_k^s, the preliminary binary map $I_k^s[x,y]$ and support value $V_k^s[x,y]$ are computed. N_k^s NSCT coefficients with the max support value are selected as the feature vector F_k^{s1}, and N_k^s NSCT coefficients with the support value 0 are randomly selected as the feature vector F_k^{s2} . Finally, those $I_k^s[x,y]$ corresponding to the selected NSCT coefficients is regarded as the training objective O_k^{s1} and O_k^{s2} respectively.

E. SVM Training and classification

Train the SVM model. Let F_k^{s1} and F_k^{s2} be the feature vectors for training, O_k^{s1} and O_k^{s2} are the training objective. The SVM model can be obtained by training. By using the well trained SVM model, all high-frequency NSCT coefficients are classified into noise-related coefficients and edge-related ones.

F. Adaptive Bayesian thresholding

Calculate the denoising threshold for each detail subband D_k^s. In this paper, a level adaptive Bayesian threshold is used, in which an exponentially decaying inter-scale model is used to describe the inter-scale dependency of image NSCT coefficients [Wang et al. (2010)]. The level adaptive Bayesian threshold can be computed as follows:

(i) Calculate noise variance σ_n, which is estimated from the subband by the robust median estimator

$$\sigma_n = \frac{\text{median}(|C(x,y)|)}{0.6745}; \qquad C(x,y) \in D_J^H \tag{2}$$

(ii) Perform an estimation of the signal variance σ_k^s (k = 1, 2,…. J; s = 1, 2,….H) for the noisy coefficients of each detail subband D_k^s, using

$$\sigma_k^s = \max(0, \frac{1}{mn} \sum_{x=1}^{m} \sum_{y=1}^{n} D_k^{s^2}(x,y) - \sigma_n^2) \tag{3}$$

Here, m and n are image size.

(iii) Calculate discriminating threshold σ_{th} by exploiting the near exponential prior of the NSCT coefficients across scales

$$\sigma_{th} = \frac{\sigma_n \sum_k 2^{-k} \sigma_k^s}{\sum_k 2^{-k} k^2} \tag{4}$$

where k is the current scale.

(iv) Calculate denoising threshold T(k; σ_k^s) for each detail subband if $\sigma_k^s < \sigma_{th}$

$$T(k, \sigma_k^s) = 2^{\frac{k - \frac{J}{2}}{J}} . \frac{\sigma_n^2}{\sigma_k^s} \tag{5}$$

where k is the current scale, J is the largest scale (or coarsest) undergoing denoising.

(v) Process the noise related NSCT coefficients in high frequency subbands with soft thresholding as follows:

$$\hat{C}_k^s(x,y) = \begin{cases} \text{sgn}(C_k^s(x,y))(|C_k^s(x,y)| - T), & |C_k^s(x,y)| \geq T \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

where k = 1, 2,…. J; s = 1, 2,….H

G. NSCT Reconstruction

Perform the inverse NSCT transform on the denoised NSCT high frequency components and the low pass component to reconstruct the denoised image.

H. Colour Image denoising

While processing colour images, the RGB colour image is first converted to the YUV space. This is because the RGB colour space suffers from high correlation among the three planes, and the transformation from RGB to YUV space is simpler. Each channel is extracted and the same process flow is followed for denoising for each channel.

III. Simulation Results

The proposed method was simulated for standard 8-bit grayscale images such as Cameraman, Lena, House, Boat and Peppers as well as for standard colour images such as Barbara, Peppers, Parrot, Mandrill and Tower. The types of noise considered in this paper were Salt and Pepper, Gaussian, Poisson and Speckle (multiplicative) noise. 'dmaxflat' was used as the directional filter for NSCT decomposition. 3-level NSCT decomposition was performed and the method resulted in good observations. The visual quality of the denoised image obtained using the proposed method is satisfactory. The PSNR value was chosen as the parameter to evaluate objective quality (Table I and II). Table III shows denoised outputs.

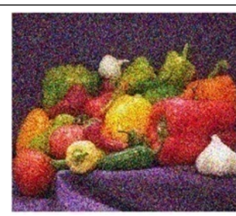
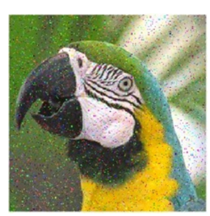
Table I: PSNR Values (in db) for Various Grayscale Images

Image	Gaussian			Salt & Pepper	Poisson	Speckle
Noise variance	10	20	30			
Lena	28.61	27.92	25.53	29.39	28.32	28.90
House	28.52	28.34	26.26	30.13	28.27	29.56
Peppers	27.65	27.46	25.34	29.20	28.32	29.45
Barbara	28.24	27.82	25.74	28.92	28.12	29.26
Cameraman	27.52	26.94	25.42	28.02	27.95	27.92

TABLE II: PSNR VALUES (IN DB) FOR VARIOUS COLOUR IMAGES

Image	Gaussian	Salt & Pepper	Poisson	Speckle
Parrot	51.45	53.99	51.32	52.12
Peppers	52.24	54.23	52.11	53.49
Barbara	50.13	51.72	50.21	50.82
Tower	52.35	53.66	52.22	52.79
Mandrill	50.11	51.25	50.15	51.13

TABLE III. DENOISING OF GRAYSCALE AND COLOUR IMAGES FOR VARIOUS TYPES OF NOISES

Description		Original image	Noisy image	Denoised image
Image	Noise type			
House	Gaussian noise of variance σ = 30			
Cameraman	Speckle noise			
Peppers	Poisson noise			
Parrot	Salt and pepper noise			

IV. CONCLUSION

Many works on image denoising are noise dependent and performs well for a particular type of noise. The proposed method has the advantage of achieving a good visual quality with very less quantity of disturbing artifacts. The method utilizes the directional properties of NSCT to preserve the information bearing structures such as edges and the excellent classification properties of SVM to classify the noisy pixels from the non-noisy ones. This technique using NSCT and SVM achieves high performance in terms of quality and clarity, irrespective of the type of noise.

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