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Noise Removal in Images in the Non Subsampled Contourlet Transform Domain Using Orthogonal Matching Pursuit

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ABSTRACT: Developing an efficient method of removing noise from digital images before processing them for further analysis, is a significant process in image processing. Ample algorithms are available, but they work well under certain assumptions, and has pros and cons. In this paper, a technique of noise removal from digital images is proposed where the image is first transformed to the nonsubsampled contourlet transform (NSCT) domain and then support vector machine (SVM) is used for classifying noisy pixels from the edge related ones. The spatial relationships between pixels in the original image are well represented by the coefficients in the NSCT domain. These spatial relationships represent features of the image and should be retained as much as possible during denoising. The NSCT detail coefficients are extracted and feature vector for a pixel in the noisy image is formed by the spatial regularity in NSCT domain. Then the SVM model is obtained by training, and the NSCT detail coefficients are classified into two classes (noise related coefficients and non-noisy ones) using the model. Finally, the denoising is done by the orthogonal matching pursuit algorithm (OMP), which is an iterative greedy algorithm that finds the most correlated estimate of the denoised image by minimizing the residuals at each step. 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. Objective evaluations such as peak signal to noise ratio (PSNR), structural similarity index (SSIM) and root mean square error (RMSE), reveal the superiority of the proposed method over the state of art denoising algorithms.

KEYWORDS: Image denoising; Non subsampled contourlet transform (NSCT); Support vector machine (SVM); Orthogonal matching pursuit.

I. INTRODUCTION

Image denoising has been a well versed problem in the area of image processing. The current research has not yet reached the lower bound on the mean squared error of the denoised result. Despite the phenomenal recent progress in the quality of denoising algorithms, there is still some space for improvement for a wider class of general images, and at certain signal-to-noise levels. Image denoising leads to a breakdown of image quality at higher sensitivities in two ways: noise levels increase and fine detail is smoothed out by the more aggressive noise reduction. Indeed, numerous contributions in the past 50 years or so address this problem from many and diverse points of view. Wavelets have been the most prominent tool in image processing nowadays. Current trend explores the use of more efficient, multidirectional and overcomplete transforms such as curvelets, contourlets, bandelets, shearlets etc. Particularly, the contourlet transform has shown to be effective in image denoising. However, the constructive variant of the contourlet transform, called the non subsampled contourlet transform (NSCT) mostly finds application in image fusion and enhancement. Detailed study on NSCT states that it provides an excellent representation of directional features of an image. Since image denoising aims at preserving the edge features of an image while reducing noise, the use of NSCT for image denoising can be of great significance.

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II. RELATED WORK

All image denoising algorithms are intended to share the same property: to keep the meaningful edges and remove the less meaningful ones. Image denoising is an open problem and has received considerable attention in the literature for several decades. Rather than spatial domain filtering techniques, wavelet domain techniques showed superiority in image denoising.

Pizurica and Phillips [1] developed a novel **wavelet domain denoising** method for subband-adaptive, spatially-adaptive and multi valued image denoising. Shi et al. [2] presented an image denoising method based on multiscale wavelet thresholding and bilateral filtering. The principle of de-noising in **compressive domain** [3] is to decompose a noisy signal from time domain into compressive domain where the coefficients are associated with different scales and time. The coefficients of the noises, have low value in coefficient domain while the coefficients of the signal have high value, which makes it possible to remove noises from noisy signal by zeroing the coefficients below a thresholding value and to reconstruct the signal. Shulei Wu et al. [4] introduced coefficients of wavelet transform into a greedy strategy, combine **orthogonal matching pursuit** (OMP) algorithm with SVD decomposition to train these coefficients with the redundant dictionary of discrete cosine transform (DCT).

Recently, several more effective transforms with good directionality and anisotropy are proposed, such as Curvelet, Contourlet…After Contourlet decomposition, the noise has small Contourlet coefficients in high frequency bands while the features have large coefficients, so reducing noise is to eliminate the smaller coefficients. So a threshold is set to distinguish the noise and the feature in some denoising methods using Contourlet [5,6]. The contourlet transform translational invariance of the Gibbs effect will be introduced during the image processing. In 2006, A. L. Cunha et al. [7] created **nonsubsampled Contourlet transform** (NSCT) by using nonsubsampled pyramid decomposition and nonsubsampled filter bank. Image de-noising algorithm using adaptive bayes threshold by subband based on nonsubsampled contourlet transform [8] was proposed in 2013. The method can adaptively adjust the threshold, so as to effectively remove the image noise and Gibbs artifacts preserving image detail, and get better visual effects and higher PSNR values. An image denoising algorithm in the nonsubsampled contourlet transform (NSCT) domain by combining with generalized cross validation (GCV) principle [9] was proposed by Xianwei Fu et al.

A mixed image denoising method based on non-local means (NL-means) and adaptive Bayesian threshold estimation in nonsubsampled contourlet transform (NSCT) was developed [10]. Considering strong correlations between the parent and child coefficients of NSCT, and inter-scale and intra-scale dependency, a method for image denoising in NSCT domain by using locally adaptive bivariate shrinkage algorithm was proposed [11]. Later on, spatially adaptive threshold based on Context-Modeling was proposed because of having considered neighbouring coefficients so that it can adjust to coefficient characteristics [12]. Also the improved spatially adaptive threshold method was applied to the nonsubsampled contourlet transform.More recently, image denoising algorithms using **Support Vector Machine** (SVM) have been developed. Cheng et al. [13] proposed a manipulation of wavelet coefficients for the suppression of noise in images by fusing the wavelet transform with support vector regression (SVR). Based on un-decimated discrete wavelet transform, Wang et al. [14] introduced a new wavelet based image denoising using least square- support vector machine (LS-SVM). Later, the same was developed in the NSCT domain and found better results for denoising [15].

III. SCOPE OF THE WORK

The search for efficient image denoising methods is still a valid challenge at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. All show an outstanding performance when the image model corresponds to the algorithm assumptions but fail in general and create artifacts or remove image fine structures. For instance, many denoising algorithms operate on the assumption that the noise level is known a priori, which in fact is not valid in practical circumstances. The main focus of this thesis is to achieve a high visual quality of the reconstructed image with minimum disturbing artifacts, while analytically ensuring the same in terms of qualitative metrics, with no information on the noise known apriori.

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IV. PROPOSED ALGORITHM

The proposed method works well for both gray scale images as well as colour images. For colour images, each channel of the image in the RGB colour space is extracted and the process flow for denoising is followed. The process flow is illustrated in Fig. 1. In the figure, the NSCT domain is illustrated in blue colour. The NSCT of the noisy image gis initially taken which transforms the entire processing in NSCT domain. All the processing is done in the NSCT domain and finally the altered coefficients are reconstructed back to form the denoised image.

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).

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

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 and support value are computed. A number of NSCT coefficients with the max support value are selected as the feature vector F_1, and an equal number of NSCT coefficients with the support value 0 are randomly selected as the feature vector F_2. Finally, the binary values corresponding to the selected NSCT coefficients are regarded as the training objective O_1 and O_2 respectively.

E. *SVM Training and classification*

Train the SVM model. Let F_1 and F_2 be the feature vectors for training, O_1 and O_2 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. The noisy pixels thus classified are replaced by their median value and the non-noisy ones are kept as such.

F. *Noise level estimation*

A patch-based noise estimation algorithm using principal component analysis (PCA) was proposed by Xinhao Liu et al. [16]. An iterative framework is developed to select weak textured patches from the noisy image with different noise levels. The goal of noise level estimation is to calculate the unknown standard deviation, σ_n, given only the observed noisy image. The noise level can be estimated easily if we can decompose the minimum eigen value of the covariance matrix of the noisy patches as in eq. (2).

$$\lambda_{min}(\Sigma_y) = \lambda_{min}(\Sigma_z) + \sigma_n^2 \qquad \text{eq. (2)}$$

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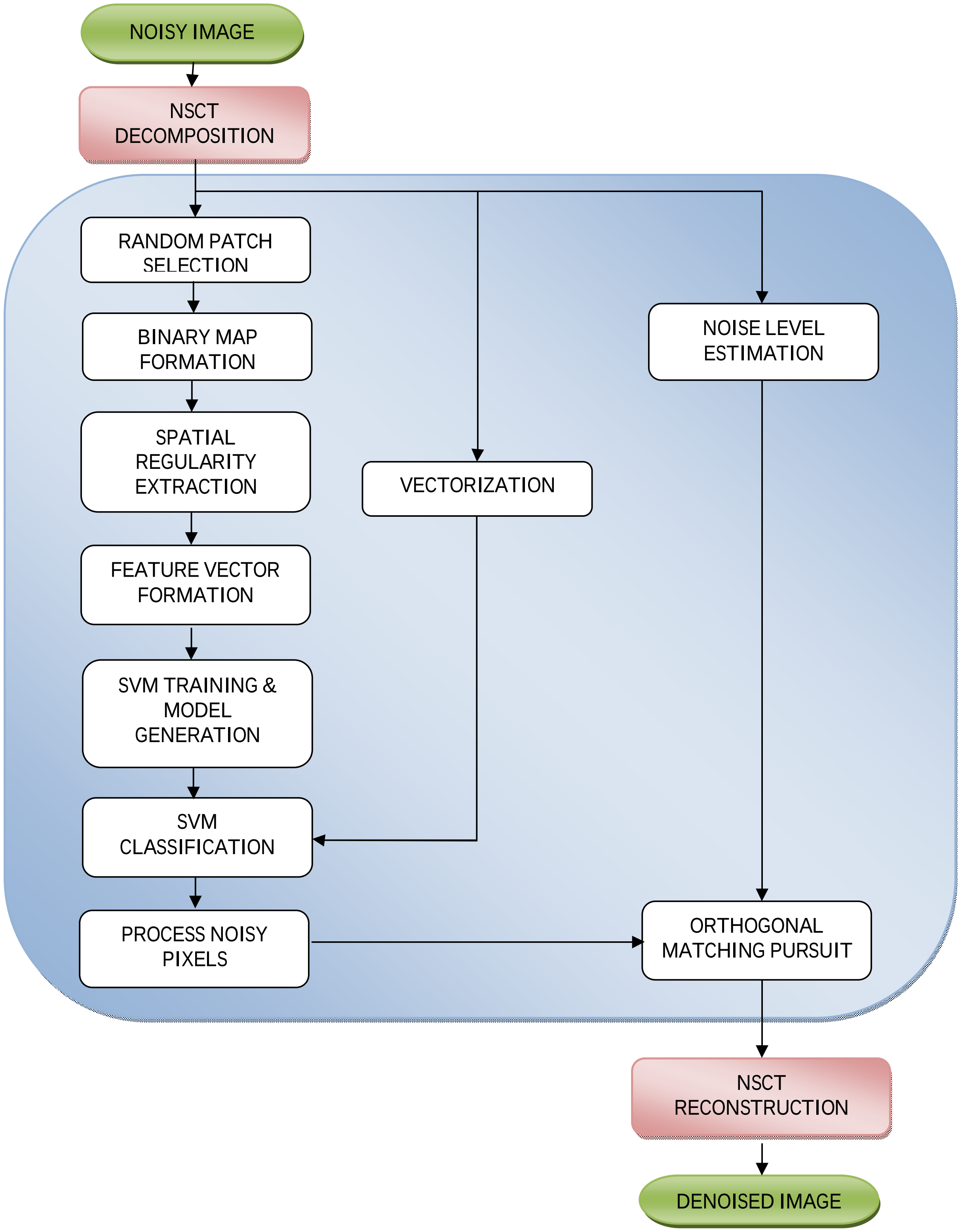

Fig. 1: Process flow of the proposed method

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where **Σy** signifies the covariance matrix of the noisy patch, **Σz** denotes the covariance matrix of the noise-free patch, and $\lambda_{min}(\mathbf{\Sigma})$ represents the minimum eigen value of the matrix **Σ**.

Noise level can be estimated if weak textured patches can be selected from the noisy image. The weak textured patches are known to span only low dimensional subspace. The minimum eigen value of the covariance matrix of such weak textured patches is approximately zero. Then, the noise level can be estimated simply as in eq. (3).

$$\sigma_n^2 = \lambda_{min}(\Sigma_{y'}) \qquad \text{eq. (3)}$$

where **Σy'** is the covariance matrix of the selected weak textured patches.

G. *Image recovery using OMP algorithm*

The NSCT detail coefficients resulting from the classified and processed sub images are then taken in sparse form. This is then applied to the Orthogonal Matching Pursuit (OMP) algorithm along with the estimated noise factor. The initial estimate is chosen as a random measurement matrix, usually the Gaussian random matrix. The iterative greedy OMP algorithm finds the most correlated estimate of the denoised image by minimizing the residuals at each step until the stopping rule is satisfied. It is necessary to block and vectorize the sub images being input to OMP, meanwhile reverse procedures should be carried out to acquire the whole denoised images. That means the de-noising is realized at every block, and executed block by block.

H. *NSCT Reconstruction*

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

V. 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 and Poisson noise. 'dmaxflat' was used as the directional filter for NSCT decomposition. 3-level NSCT decomposition was performed and the method resulted in good observations.

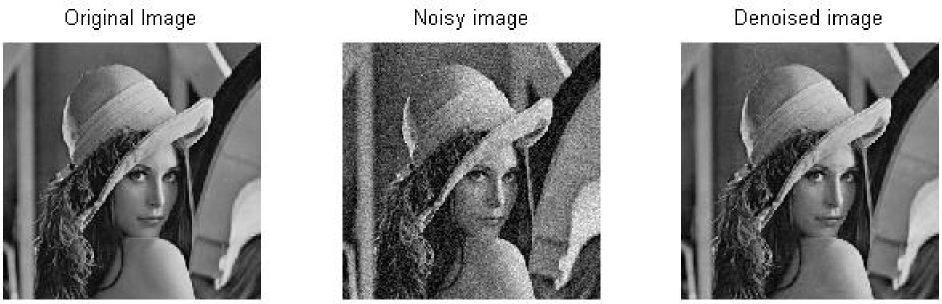

Fig. 2. Denoising results on 256 x 256 Lena grayscale image

The visual quality of the denoised image obtained using the proposed method is found to be superior to other well known denoising methods. The denoised image was found to have minimal disturbing artifacts while most of the fine features of the image where preserved. Peak Signal to Noise Ratio (PSNR), Root Mean Square Error (RMSE) and Structural similarity Index Measurement (SSIM) were evaluated for denoised results. Moreover, the noise level of the output denoised image is estimated using the PCA based noise level estimation technique [16]. The noise level is found to be reduced when compared to the noise level of the input noisy image.

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Fig. 3. Denoising results on Parrot image

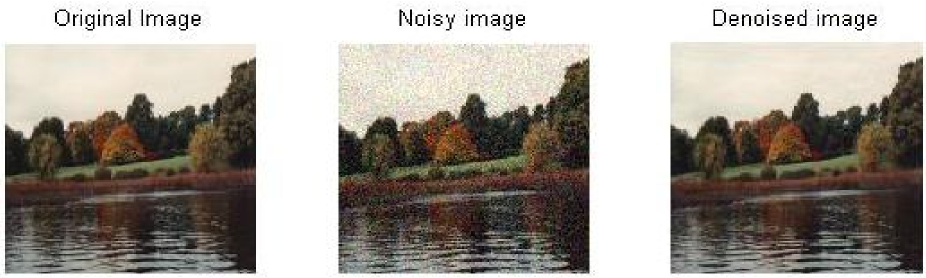

Fig. 4. Denoising results on Autumn image

Apart from the standard natural images, this method was implemented on IR image, radar image and medical images such as ultrasound and MRI image. The proposed method showed significant denoising in all these test images. This proves the utility of the proposed method in denoising any kind of image available.

Table 1. Output PSNR for standard cameraman image contaminated with Gaussian noise of variance σ = 10 with available directional filters

Type of Directional Filter	**PSNR(dB)**
haar	35.05
sk	28.69
dmaxflat	**38.61**
cd	19.08
pkva	37.07
vk	37.97

The type of directional filter was chosen from the PSNR measurements obtained as presented in Table 1. The 'dmaxflat' directional filter was found to produce denoised images with high PSNR, and hence was used throughout the implementation.

Table.2. Quality metrics for various grayscale images affected by Gaussian (σ=20), Salt & Pepper and Poisson noise

	Gaussian				**Salt & Pepper**				**Poisson**			
	PSNR	**RMSE**	**SSIM**	**NL**	**PSNR**	**RMSE**	**SSIM**	**NL**	**PSNR**	**RMSE**	**SSIM**	**NL**
Lena	33.7106	5.2603	0.9002	0.8679	32.8113	5.8341	0.9014	1.0259	32.5301	6.0261	0.9279	1.3213
House	34.0009	5.0874	0.9214	0.7912	33.9061	5.1432	0.9117	0.9870	32.3629	6.1432	0.9314	1.8765
Peppers	33.9346	5.1264	0.9053	0.8986	33.6981	5.2679	0.9283	0.8325	31.5652	6.7341	0.9123	0.9318
Barbara	32.8422	5.8134	0.8937	1.7902	32.5163	6.0357	0.8912	0.9135	31.2821	6.9572	0.8914	0.7314
Cameraman	33.1338	5.6215	0.9148	1.0205	32.5644	6.0023	0.8996	0.9025	31.8291	6.5326	0.9011	09635

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The PSNR, RMSE, SSIM and the output noise level were computed for the denoised images in the case of grayscale and colour images for Gaussian, Salt & pepper, and Poisson noise. Table 2 and 3 summarizes the quality metrics obtained when the images were contaminated with different types of noises. The proposed method is found to show excellent results irrespective of the type of noise.

Table 3. Quality metrics for various colour images affected by Gaussian (σ=20), Salt & Pepper and Poisson noise

	Gaussian				Salt & Pepper				Poisson			
	PSNR	RMSE	SSIM	NL	PSNR	RMSE	SSIM	NL	PSNR	RMSE	SSIM	NL
Parrot	37.9188	3.2405	0.9524	1.4233	37.9317	3.2356	0.9435	0.7323	36.6213	3.7625	0.9325	0.9945
Autumn	36.6334	3.7725	0.9450	0.7303	36.4455	3.8894	0.9215	0.4214	36.2542	3.9249	0.9167	0.9821
Peppers	36.4550	3.8394	0.9432	1.3942	36.0305	4.0273	0.9053	1.4223	35.8489	4.1124	0.9006	1.5641
Tower	36.2140	3.9431	0.9510	0.9606	35.9403	4.0524	0.8965	1.7967	35.5716	4.2458	0.8862	1.8972
Mandrill	35.7402	4.1642	0.9103	0.8910	35.2894	4.3860	0.9005	1.2358	35.1268	4.4689	0.8874	1.6548

The proposed method not only has a superior visual quality but also excels in terms of objective evaluation parameters, when compared with other state-of-the-art denoising techniques. The PSNR values obtained by the proposed method were plotted along with other denoising methods subject to the same noise conditions. The plot is as shown in Fig. 5.

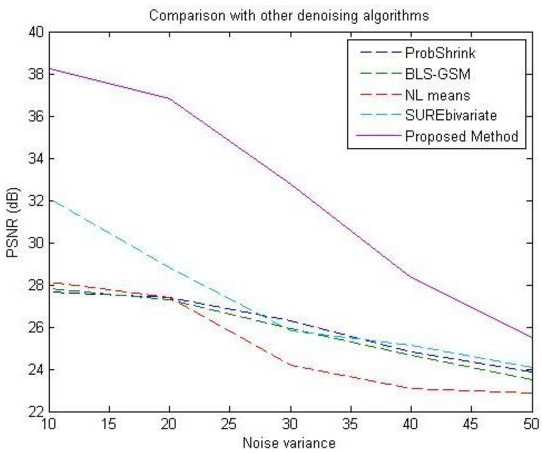

Fig. 5. Plot of output PSNR for increasing noise variance of Gaussian noise

VI. CONCLUSION AND FUTURE WORK

The use of non subsampled contourlet transform (NSCT) in image denoising has been explored. Since NSCT provides an excellent representation of directional features of an image, image denoising in NSCT domain excels in preserving the edge features of an image while reducing noise. Many denoising algorithms operate on the assumption that the noise level is known a priori, which in fact is not valid in practical circumstances. The proposed method has achieved a high visual quality of the reconstructed image with minimum disturbing artifacts, while analytically ensuring the same in terms of qualitative metrics, with no information on the noise known apriori. The method utilizes the directional properties of non subsampled contourlet transform to preserve the information bearing structures such as edges and the excellent classification properties of support vector machine to classify the noisy pixels from the non-noisy ones. Finally, the best estimate of the image is iteratively found out by the Orthogonal Matching Pursuit algorithm. Experimental results show the superiority of the proposed method over state-of-the-art denoising techniques.

The proposed method can be extended to work for speckle noise. If the input noisy image is subjected to log-transformation, the noisy component becomes additive and the proposed method can be implemented. Later, it can be

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nullified by taking the exponential of the result. Here, the challenge is to take the initial estimate to the OMP algorithm. Also, computation and time optimization techniques can be sought for enabling the method in online processing.

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BIOGRAPHY

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