BM3D Image Denoising using Learning-based Adaptive Hard Thresholding

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Abstract: Block Matching and 3D Filtering (BM3D) is considered to be the current state-of-art algorithm for additive image denoising. But this algorithm uses a fixed hard threshold value to attenuate noise from a 3D block. Experiment shows that this fixed hard thresholding deteriorates the performance of BM3D because it does not consider the context of corresponding blocks. We propose a learning based adaptive hard thresholding method to solve this problem and found excellent improvement over the original BM3D. Also, BM3D algorithm requires as an input the value of noise level in the input image. But in real life it is not practical to pass as an input the noise level of an image to the algorithm. We also added noise level estimation method in our algorithm without degrading the performance. Experimental results demonstrate that our proposed algorithm outperforms BM3D in both objective and subjective fidelity criteria.

1 INTRODUCTION

Image denoising is the process of reducing the noise artifact from a noisy image. This domain of image processing is very popular and old because images are often contaminated by different types of noise due various factors, including the quality of image sensor. Reducing noise from these images is very important, as noisy images in different imaging applications can degrade the performance of that system.

Noise is a random variation of brightness or color information in images and it can be additive or multiplicative. Additive noise is independent of image signal and added to the image. It can be generally modeled as:

$$v(x) = u(x) + \eta(x) \tag{1}$$

where $u(x)$ is a original signal and $\eta(x)$ is the noise of the channel. On the other hand, multiplicative noise gets multiplied into the image signal. It can be generally modeled as:

$$v(x) = u(x) \times \eta(x) \tag{2}$$

Our study focused on Additive White Gaussian Noise (AWGN). AWGN refers to the additive noise which has constant power spectral density and follows a Gaussian (normal) distribution.

Image denoising can be performed either in the spatial domain or in the frequency domain. In spacial domain, denoising is done by applying filter directly to the intensity values of the image. On the other hand, in frequency domain techniques, an image is transformed to the frequency domain and then the filtering operations are performed there, and the resulting denoised signal is transformed back into the spatial domain.

From the early stage of image denoising, spatial domain denoising was very popular because there is no overhead for domain transformation and it is very simple. Some of the basic spatial domain filters are Mean Filter, Median Filter and Gaussian Smoothing (Gonzalez and Woods, 2008). In these filtering techniques every pixel is non-adaptively adjudicated based on the surrounding pixels. It does not take into account whether the pixel is from a smooth region or an edge. So edges become blurred in these methods. To solve this problem Perona and Malik proposed an edge preserving image denoising technique called Anisotropic Diffusion (Perona and Malik, 1990). The main idea of this technique is to first identify whether a pixel is from a smooth region or an edge and then denoise it.

All of these spatial denoising techniques are pixel-based denoising schemes. Non-Local Meas (NLM) changed this idea to patch-based denoising scheme (Buades et al., 2005). It is the most successful spatial domain image denoising scheme. Instead of fil-

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tering a single pixel based on its neighboring pixels, it works with patches in a particular window. In this algorithm, a block/patch is defined around a particular pixel, referred as the reference patch. A search window is also defined around the pixel where similar patches of the reference patch is searched. The patches are given a weight based on its similarity with the reference patch. The center pixel of the reference patch is then denoised by weighted averaging of all the patch center pixels. A number of improvements has been proposed over NLM algorithm which have achieved a slight better accuracy over the original NLM. Some of the algorithms are: SSIM-Based Non Local Means (Rehman and Wang, 2011), Adaptive Non-Local Means (Thaipanich et al., 2010) and Non-Local Medians (Chaudhury and Singer, 2012).

In frequency domain denoising, the basic filtering technique is Low Pass Filter (Gonzalez and Woods, 2008) which allows to pass the signal with frequencies lower than a cutoff frequency and attenuates signals with frequencies higher than the cutoff frequency. Another popular filter is Weiner Filter (Wiener, 1949). It tries to estimate the noise from a degraded image and denoise it based on this estimation. The current state-of-art denoising technique is Block Matching and 3D Filtering (BM3D). Detailed description of BM3D is described in Section 2.1. A number of improvements has been proposed over the BM3D algorithm. Dabov et al. introduced PCA in BM3D and proposed another algorithm, BM3D-SAPCA (Dabov et al., 2009). They have also extended BM3D for color image denoising (Dabov et al., 2007b) and video denoising (Dabov et al., 2007a). Dai et al. added adaptive distance hard thresholding in BM3D (Dai et al., 2013) and Mittal et al. adapted machine learning based techniques to predict the noise level parameter used in BM3D (Mittal et al., 2012). Recently structural similarity is used in Wiener filtering part of BM3D instead of using traditional MSE (Hasan and El-Sakka, 2015).

Although BM3D achieves excellent performance in reducing Additive White Gaussian Noise, it posses some limitations as well. Our main study focused on finding these limitation and provide possible solutions for them. BM3D algorithm relies on a user provided noise level for each noisy image which is not possible for real time systems. This noise level is very important for estimating the denoised image. We have incorporated a noise level estimation mechanism without hampering the performance in this algorithm to convert this as an automated system. Also, in BM3D a hard thresholding is used for any block of the noisy image. We have illustrated that this thresholding depends on image block's texture and noise level. Tuning this threshold can improve the performance of BM3D. Thus we have proposed a learning-based adaptive hard thresholding mechanism where each block uses different thresholds based on their context. From a set of training images, a classifier is trained by providing the image block as a feature and their best threshold as a label. From a test image, the best threshold of its different block is predicted from this classifier. This best threshold is used in the algorithm to denoise that particular block. Experiments show that this learning-based adaptive hard thresholding improves the performance of BM3D much over the original BM3D algorithm.

2 RELATED WORK

In recent years Block Matching and 3D Filtering (BM3D) becomes the most popular image denoising technique. Dabov et al. first proposed the idea in 2006 (Dabov et al., 2006) and explained it thoroughly in 2007 (Dabov et al., 2007c). BM3D achieves excellent performance in reducing Additive White Gaussian Noise (AWGN). It has achieved the state-of-the-art denoising performance in terms of both peak signal-to-noise ratio and subjective visual quality. In our work we have tried to highlight the limitations of this algorithm and propose modifications to improve the performance of this method.

2.1 Block Matching and 3D Filtering (BM3D)

BM3D follows the concept of patch-based denoising mechanism where instead of denoising one single pixel, a patch/block of pixels are denoised at a time, a concept adapted from the Non-Local Means (NLM) algorithm (Buades et al., 2005). It was the state-of-the-art algorithm for image denoising before BM3D, where a single patch is denoised by finding its similar patches from a given window. BM3D also extended it by denoising an image using two almost identical steps. In the first step, a basic estimate of the noisy image is generated. This basic estimate is then passed to the second step to generate the final denoised image. The block diagram of this algorithm is shown in Fig. 1.

2.1.1 BM3D First Step

The first step of BM3D is known as the hard thresholding step because a hard thresholding is used to eliminate noise from the image. First, the noisy image

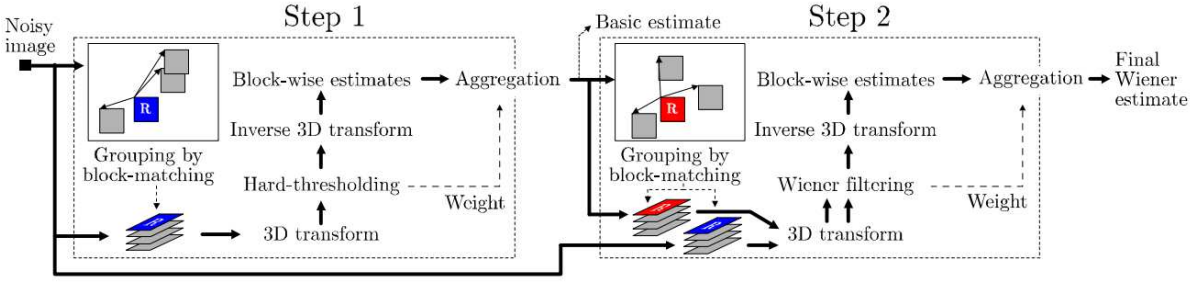


Figure 1: BM3D Block Diagram (Dabov et al., 2007c).

is divided into a number of patches or blocks. A window is defined centering each patch also referred as the reference patch and within this window it searches for the patches similar to the reference patch. As the initial image is noisy, calculating similarity between noisy blocks may degrade the performance. So, first the blocks are filtered by using 2D transformation and then the obtained coefficients are hard thresholded. Next euclidean-distance between the reference block and each of the other blocks are calculated. This similarity measurement is called d-distance. From this d-distance values, the similar noisy patches are grouped together into a set, $S^{ht}_{x_R}$. From this set, the noisy blocks are grouped together in a form of 3D array which we denote $Z_{S^{ht}_{x_R}}$. A 3D linear transform is applied on this 3D blocks and hard thresholding is applied on the obtained coefficients, called collaborative filtering. This thresholding attenuates the noise. An inverse 3D transform is applied to get back to the spatial domain. Equation (3) shows the block-wise estimation of a 3D block.

$$\hat{Y}^{ht}_{S^{ht}_{x_R}} = {\tau^{ht}_{3D}}^{-1}(\Upsilon(\tau^{ht}_{3D}(Z_{S^{ht}_{x_R}}))) \quad (3)$$

where Υ is a hard-threshold operator and $\hat{Y}^{ht}_{S^{ht}_{x_R}}$ is stacked block-wise estimation of noisy blocks in set $S^{ht}_{x_R}$. The final operation in the first step of BM3D is to aggregate all the estimated blocks together. Each of the estimated sets contain a number of blocks and these blocks contain one or more same pixel locations. That means, a single pixel can have more that one estimation. So to get the final estimation all these estimations are aggregated together by a weighted averaging method. The basic estimate of the noisy image is then passed to the second step of BM3D to generate the final estimation of the noisy image.

2.1.2 BM3D Second Step

The basic estimated image coming from the first step has significantly attenuated noise, compared to the input image. This image is used in the second step as a reference denoised image of the input image. The second step of BM3D is identical to the first step. At first the similar basic estimated blocks are grouped together for any reference block. But here, instead of using the thresholding-based d-distance, a normalized squared l^2-distance is used to calculate the similarity. The basic estimated blocks and noisy blocks from input image are stacked. Wiener shrinkage coefficients are generated by applying a 3D transform on the basic estimated group. The 3D transform coefficients of noisy blocks are multiplied, element-by-element, with the Wiener shrinkage coefficients. This is called Wiener collaborative filtering. An inverse 3D transform is applied to get the estimated pixel values. These estimated blocks are then aggregated together to generate the final global estimated image. Aggregation is done by a weighted averaging of the estimated blocks similar to first step.

3 MAIN IDEA

In our study and experiments, we tried to overcome the limitations of BM3D. We focused on two limitations of BM3D which are:

1. **Noise Level:** In the implementation of BM3D algorithm, we have found that the actual noise variance of the image is provided to the algorithm which is used in both first and second step. In real time systems, the actual noise variance is not practical to be provided as an input.
2. **Fixed Hard Thresholding:** In the first step of BM3D algorithm, a hard threshold is used to attenuate noise from the 3D blocks. This threshold is fixed for all the blocks. Using fixed threshold value deteriorates the performance of this algorithm because for smooth region and textured region thresholding value should not be same.

We have done several experiments to solve these two limitations and developed our proposed algorithm. Below is a detailed description of how we found our solution to these limitations.

3.1 Automated Noise Estimation

While using the authors' provided matlab software of BM3D, we have found that the true noise level (standard deviation) of input noisy image is provided as input. Also, we have observed that if the noise level is changed a little, then the performance of the algorithm varies a lot. So, we can say that the performance of the BM3D algorithm provided by the BM3D authors heavily depends on the value of the input parameter.

In our proposed algorithm, we created an automated noise estimation system where the noise level of an input image is calculated first. We found that our noise level estimation is very close to the actual noise level, hence eliminating such input without degrading the performance.

For the noise level calculation, we have taken the idea from the 2D adaptive Wiener filtering (wiener2) algorithm (Lim, 1990). In this algorithm, image noise level is estimated based on the local variance of the image. The local mean and variance around each pixel are calculated using Equation (4) and (5), respectively

$$\mu(a,b) = \frac{1}{MN} \sum_{x,y \in \eta} I(x,y) \tag{4}$$

and

$$\sigma^2(a,b) = \frac{1}{MN} \sum_{x,y \in \eta} I^2(x,y) - \mu^2(a,b), \tag{5}$$

where η is the $N \times M$ local neighborhood of each pixel in the image I. The noise variance is then calculated by averaging all the local estimated variance using Equation (6)

$$v^2 = \frac{1}{MN} \sum_{x,y \in \eta} \sigma^2(x,y), \tag{6}$$

where $\sigma^2(x,y)$ is the local estimated variance calculated from Equation (5). From this noise variance, Equation (6), we can calculate the standard deviation (sigma) of the noisy image. We have experimented using various neighborhood and found that 2×2 neighborhood produces the closest estimation to the actual noise level.

3.2 Context-based Hard Thresholding

In the first step of BM3D algorithm, a hard thresholding is applied on the 3D noisy blocks during the collaborative filtering. This hard thresholding attenuates the noise of corresponding blocks; see Section 2.1.

Note that, the hard threshold operator Υ is fixed for every blocks of the image.The BM3D authors used a fixed value, $\Upsilon = 2.7$. For image having noise level greater than 40 they have changed this value to $\Upsilon = 2.8$. This threshold is used to attenuate the noise of corresponding block. But using a fixed level of threshold value is not quite a good choice, as blocks with different properties should have different threshold values.

We started our experiment to find out whether different blocks should use different threshold values or not. First, we took two different images, one with high texture and the other with smooth region and then applied same level of noise to both of them. Next we applied BM3D algorithm on them using various threshold values and took the best denoised image. We observed that different threshold values are used to generate best denoised image in each case. The experiment is also done using an image with various noise levels and observed that the best threshold value also changes with the noise level.

4 PROPOSED METHOD

Our proposed algorithm is divided into two main parts: *training* and *testing*. Detailed description of the algorithm is explained below.

4.1 Training

In the training phase, we developed 10 different classifier for 10 different noise levels , $\sigma = 10, 20, 30, 40, 50, 60, 70, 80, 90$ and 100. Here, image blocks are used as feature vectors and their corresponding best threshold value as a label of that vector. Below is a detailed description for training a single classifier.

4.1.1 Best Threshold Calculation

From the idea of context based hard thresholding, see Section 3.2, we know that different types of image blocks should have different threshold values. So, we conducted experiments on finding the best threshold value for any reference block.

1. To build a classifier for noise level n, we have applied AWGN with $\sigma = n$ to all input images from the database.
2. The BM3D image denoising algorithm is applied to these noisy images generated from the previous step. During collaborative filtering in the first step, we have used various threshold values for each block. In our experiments, we have used 22 different threshold values, ranging from 1.7 to 3.8 with step size of 0.1.

3. The 22 denoised blocks (based on applying various threshold values) are compared with the corresponding block in the original true image and the best among them is selected. The comparison is done based on squared euclidean distance between these two blocks.
4. The threshold corresponding to the best denoised block is considered to be the best threshold value of that particular block.
5. Every block and their best threshold value is stored in a matrix.

After taking all of the best denoised block during collaborative filtering operation, we found the generated output to be significantly better than the output of original BM3D algorithm in terms of PSNR and visual quality. To asses the performance, we have conducted this experiment and found that the PSNR is improved by about 3 decimal (on average) when the best threshold is used, for a given noise level.

4.1.2 Feature Generation

1. For any input image, each of the image block is considered as a feature vector and their corresponding best threshold value is considered as label of that feature.
2. Since we are considering blocks of size 7×7, thus each feature consists of 49 noisy pixel values.
3. In an image of size $M \times N$, a total $M \times N$ feature vectors are generated, each of length 49 features.
4. To reduce memory and time complexities, we have only taken 10% of the total features, by taking one feature and leaving the following nine features.

4.1.3 Training Features

1. The generated features and their corresponding labels are used to train a classifier that will be used in the next part of the algorithm.

In our experiment, we have used different classification techniques namely, Naive Bayes, SVM, K Nearest Neighborhood and Random Forest to find out the best classifier for our algorithm. Based on their performance we have decided to use Random Forest (RF) classification algorithm. Random forests are an ensemble learning method for classification. It is operated by constructing a multitude of decision trees (classification trees) at training time and outputting the class that is the mode of the classes of the individual trees. To classify a new object from an input vector, put the input vector down each of the trees in the forest. Each tree gives a classification which means the tree votes for that class. The forest chooses the classification having the most votes (over all the trees in the forest) (Breiman, 2001).

4.2 Testing

In testing step, the classifier developed in the training part is used to generate the appropriate threshold to be used to denoise the input image. Detailed description of the testing phase is given part by part below.

4.2.1 Noise Calculation and Classifier Selection

1. From the test image, initial noise level is calculated using the algorithm described in Section 3.1.
2. The noise is then rounded to the nearest multiple of 10. If the value is more than 100, it is clipped at 100.
3. From the 10 trained classifiers, we choose our classifier based on the noise level.

4.2.2 Feature Vector Generation

1. The noisy input image is divided into several blocks of size 7×7. These 49 noisy pixels are considered the feature vector of a single block.
2. Feature vectors are generated from all of the blocks of the noisy image.

4.2.3 Classification

1. The feature set is passed to the classifier.
2. The classifier will return the label of each feature vector.
3. Each of the noisy blocks are then assigned their corresponding best threshold value.

4.2.4 Output Generation

1. The noisy image is filtered using BM3D image denoising algorithm with our predicted noise level where in the collaborative filtering step, adaptive thresholding is applied.
2. All other operations will remain the same as in the original BM3D. After the second step of BM3D, our final denoised image is generated.

5 RESULT ANALYSIS

In this section we will compare the performance of our proposed method with the state-of-art BM3D im-

(a) Boat2 (b) Lighthouse (c) Woman (d) Sail (e) Statue (f) Model

(g) Beach (h) Bike (i) Bridge (j) Cottage

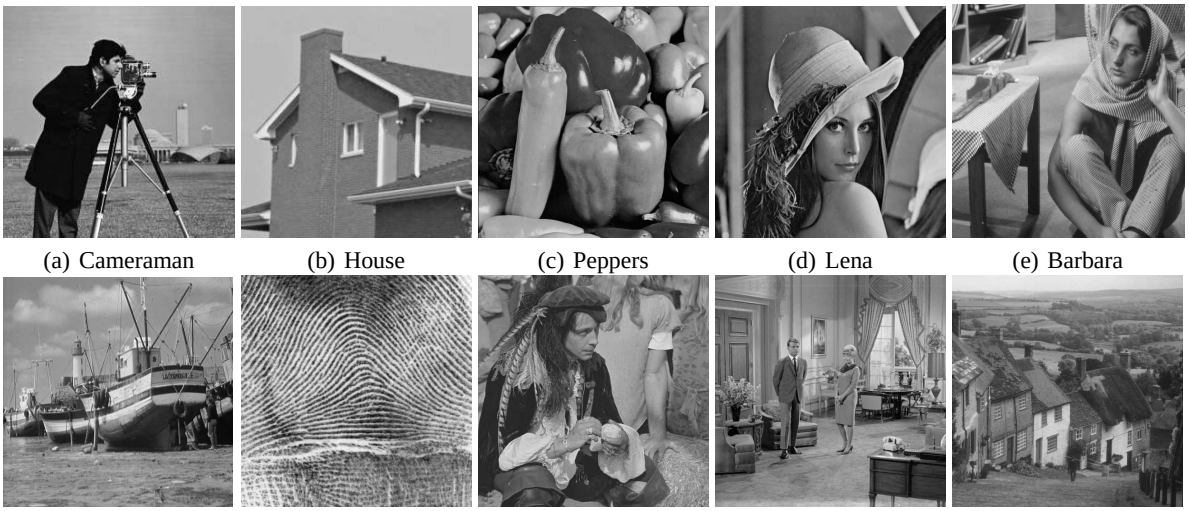
(k) Door (l) Flower (m) Raft (n) Girl

(o) Hats (p) House2 (q) Houses (r) Windows

(s) Island (t) Lake (u) Landscape (v) Lighthouse2

(w) Parrot (x) Plane

Figure 2: Training Image set (Kodak Image set).



(a) Cameraman (b) House (c) Peppers (d) Lena (e) Barbara

(f) Boat (g) Fingerprint (h) Man (i) Couple (j) Hill

Figure 3: Training Image set (Subset of BM3D Test Image set).

age denoising algorithm and the Non-Local Means (NLM) algorithm.

5.1 Experimental Setup

The performance of our proposed algorithm is conducted on two sets of images: Kodak image set and BM3D image set. For training the classifiers, we have used Kodak image set which contains 24 different grayscale images. For testing, we have taken 10 grayscale images from the BM3D image set. Both of these set have images containing textured and smooth regions. The training and test image set is shown in Fig. 2 and 3, respectively.

5.2 Performance Measurement Metrics

The performance of our experiments are measured using both subjective and objective fidelity criteria. Objective fidelity criteria gives us blind results which is good for understanding the differences between the outputs and for subjective fidelity criteria, we observed how human eyes perceiving the denoising performance.

For objective fidelity criteria, we have used two standard measurement metrics. One is Peak Signal to Noise Ratio (PSNR) which is measured by comparing the pixel intensities between original and estimated denoised image. The PSNR of an estimated image $\hat{y}$ of a true image y, is computed according to the following standard formula:

$$PSNR(\hat{y}) = 10\log_{10}\left(\frac{255^2}{\sum_{x\in X}(y(x)-\hat{y}(x))^2}\right) \quad (7)$$

The other metric is The Structural Similarity Image Measurement (SSIM) technique. SSIM is a measurement metric measuring similarity between two images (Wang et al., 2004). SSIM is first calculated between patches and the final score is given by averaging all the patch scores. The SSIM between two blocks is calculated using the following formula:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{x,y} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c2)} \quad (8)$$

where μ and σ are mean and standard deviation of a particular block and $\sigma_{x,y}$ is the co-variance between two blocks.

5.3 Parameters Selection

In our proposed method, the parameters for best windows size (for noise calculation), threshold range and classifier selection is generated empirically by experiments.

To find the best window size in automated noise estimation step (see Section 3.1), experiment is done on our training image set. We applied 10 different noise levels to these images and estimated the noise level using Equation (6). Different windows sizes are used to find out the best window size value. It is observed that for window size, 2×2, the estimated noise level is almost close to the actual noise applied on these images. Table 1 shows these results.

In our proposed method, 22 predefined threshold values are used in the collaborative filtering step of BM3D. From these threshold values,the best threshold value is used for thresholding a particular block. We have performed experiments based on different

Table 1: Comparing estimated noise with true noise based on different window size.

Noise Level	Window Size ($\eta \times \eta$)					
	2×2	3×3	5×5	7×7	9×9	11×11
10	**11.21**	14.19	16.79	18.89	20.68	22.25
20	**20.15**	22.39	24.12	25.63	26.98	28.20
30	**30.58**	31.64	32.88	34.01	35.04	35.99
40	**40.13**	41.24	42.20	43.09	43.91	44.67
50	**50.24**	51.00	51.77	52.50	53.17	53.81
60	**60.22**	60.83	61.48	62.09	62.67	63.21
70	**70.19**	70.71	71.27	71.80	72.30	72.77
80	**80.18**	80.62	81.11	81.57	82.01	82.43
90	**90.15**	90.55	90.98	91.39	91.79	92.16
100	**100.12**	100.50	100.88	101.25	101.61	101.95

Table 2: PSNR comparison for different threshold range.

Noise Level	Threshold Range (Total Number of Threshold Values)					
	2.7 (1)	2.3-3.1 (7)	2.1-3.4 (14)	1.9-3.6 (18)	**1.7-3.8 (22)**	1.5-4.0 (26)
10	34.45	35.42	35.95	36.39	**36.91**	36.93
20	31.21	32.27	32.82	33.32	**33.95**	33.98
30	29.39	30.51	31.08	31.60	**32.30**	32.33
40	27.95	29.43	30.05	30.58	**31.28**	31.31
50	27.05	28.12	28.70	29.25	**29.97**	30.02
60	26.25	27.33	27.91	28.47	**29.20**	29.25
70	25.56	26.67	27.26	27.81	**28.55**	28.61
80	24.97	26.10	26.69	27.25	**27.99**	28.05
90	24.45	25.60	26.19	26.75	**27.49**	27.56
100	23.98	24.47	25.75	26.30	**27.05**	27.12

Table 3: Performance comparison using different classifiers for testing set (Based on PSNR).

Noise Level	Naive Bayes	SVM (Linear)	SVM (Poly)	SVM (RBF)	K-NN (k)		RF (Number of Trees)		
					(1)	(5)	(5)	(10)	**(15)**
10	33.25	31.90	33.48	34.25	33.54	34.34	34.42	35.11	**35.75**
20	29.97	28.26	29.87	31.41	29.96	30.89	31.19	32.03	**32.61**
30	28.17	26.88	28.40	29.46	28.41	29.25	29.37	30.17	**30.84**
60	26.75	25.61	27.01	28.08	27.07	28.04	27.94	28.81	**29.69**
50	25.84	24.67	26.09	26.99	26.12	27.01	27.06	27.90	**28.48**
60	25.07	23.78	25.17	26.18	25.32	26.12	26.28	27.16	**27.68**
70	24.42	23.31	24.68	25.50	24.74	25.67	25.59	26.52	**27.00**
80	23.82	22.89	24.32	24.85	24.33	25.18	25.01	25.96	**26.42**
90	23.31	22.21	23.62	24.27	23.24	24.19	24.48	25.46	**25.91**
100	22.88	21.26	22.63	23.65	22.69	23.68	23.90	25.03	**25.44**
Average	26.35	25.08	26.53	27.46	26.54	27.44	27.52	28.41	**28.98**

threshold ranges to find the range which provides the best image. Table 2 shows the result of denoised image based on different threshold ranges. It can be observed that if we increase the threshold range, the performance increases. But using 22 and 26 threshold values produces almost same results. However, taking 26 threshold values increases the number of class labels. So, we have taken 22 classes to reduce the

time complexity.

Our proposed algorithm requires a classifier to train. For finding the best classifier, we have tested our method using various classifiers, such as Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbor and Random Forest. Our experiment shows that using Random Forests provides the best accuracy based on PSNR of the denoised image. Table 3 shows the performance of average denoising result on our test images.

5.4 Performance Evaluation

The performance of our proposed method is compared with the original BM3D scheme. Also we have compared with another state-of-art denoising algorithm in spatial domain namely, Non-Local Means (NLM). Table 4 and 5 shows the average PSNR and SSIM performance for all test images. The bolded values represent the best among all these algorithms. From the results, we can easily observe that our proposed algorithm achieved better performance in both PSNR and SSIM metrics.

Table 4: PSNR comparison.

Noise Level	NLM	BM3D	**Proposed**
10	33.10	34.45	**35.75**
20	29.92	31.21	**32.61**
30	27.79	29.39	**30.84**
40	26.23	27.95	**29.69**
50	25.01	27.05	**28.48**
60	24.03	26.25	**27.68**
70	23.21	25.57	**27.00**
80	22.52	24.97	**26.42**
90	21.90	24.45	**25.91**
100	21.35	23.98	**25.44**
Average	25.51	27.53	**28.98**

Table 5: SSIM comparison.

Noise Level	NLM	BM3D	**Proposed**
10	0.895	0.919	**0.942**
20	0.812	0.865	**0.903**
30	0.734	0.824	**0.875**
40	0.660	0.786	**0.854**
50	0.592	0.759	**0.827**
60	0.531	0.733	**0.807**
70	0.478	0.709	**0.789**
80	0.431	0.687	**0.773**
90	0.390	0.667	**0.758**
100	0.355	0.647	**0.744**
Average	0.590	0.761	**0.828**

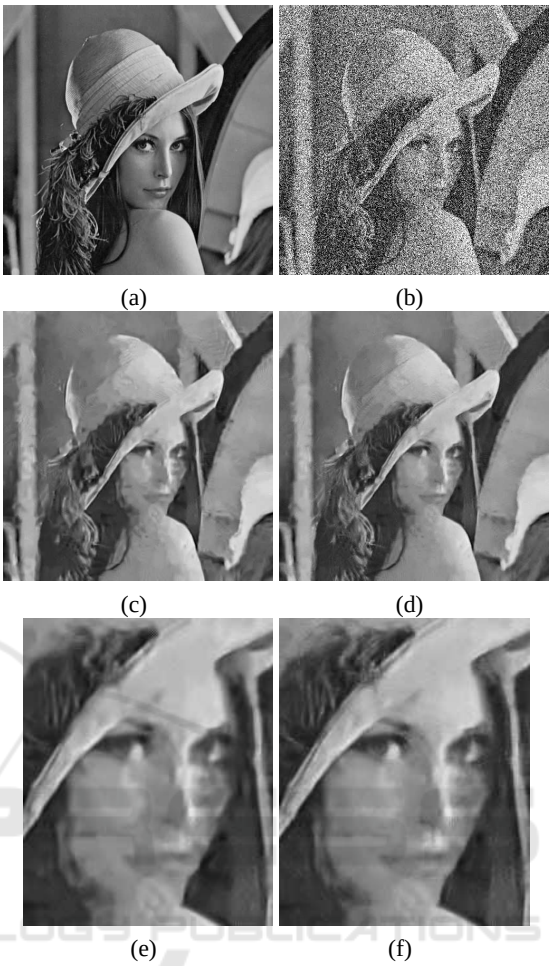


Figure 4: Performance Comparison between BM3D and Proposed Method (a) Original Image (b) Noisy Image (AWGN added with $\sigma = 100$) (c) BM3D (d) Proposed Method (e) Zoomed BM3D (f) Zoomed Proposed Method.

Fig. 4 shows a subjectuve comparison between our proposed algorithm and BM3D. We have applied AWGN noise with $\sigma = 100$ on the popular Lena image and denoised it with the original BM3D and our proposed algorithm. From the subjective viewpoint the face of Lena is more clear in denoised image produced using our proposed method, see Fig. 3(e) and 3(f).

5.5 Intensity Profile

Intensity profile is a measure for inspecting how sharp the edges are after denoising. In an intensity profile, we choose one scan line on the true image, noisy image and denoised image and plot them together to see how close the denoised profile is to the original profile. Also, it shows us how sharp the edges are after achieving denoising.

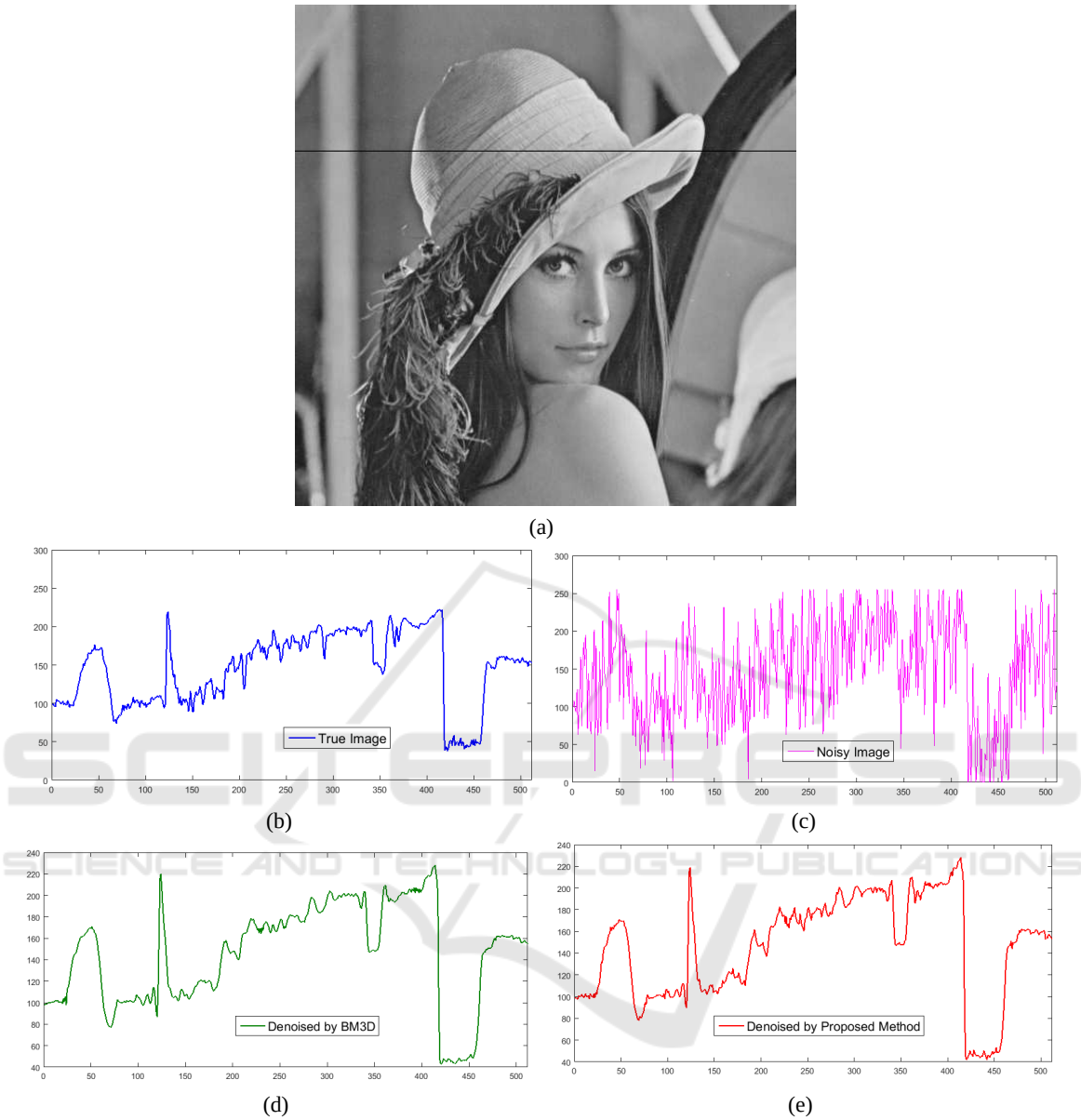


Figure 5: Intensity Profile for Lena Image at scan Line 100 ($\sigma = 50$) (a) Lena Image (b) Original Image (c) Noisy Image (Pearson correlation = 0.5220) (d) Denoised by BM3D (Pearson correlation = 0.9836) (e) Denoised by Proposed Method (Pearson correlation = 0.9934).

Let us consider the Lena image given in Figure 5(a). Here, we consider the 150^{th} row (indicated by red line) for our intensity profile calculation. A plot of this scan line is shown in Figure 5(b). We added AWGN with $\sigma = 50$ to the image and plot that scan line in Figure 5(c). We can see a lot of noise added to each of the pixel. Now, to check how close our proposed method (as well as BM3D) is to the true noise free image, we perform the same task. That is, we consider the 150^{th} row from our denoised image and BM3D's denoised image and plot them. This is shown in Figure 5(d) and 5(e) respectively.

It is clear from these plots that our proposed methods signal is closer to the true signal versus BM3D counterpart. Also, the Pearson correlation between the intensity profile of the original image and the proposed method is higher compared to BM3D.

6 CONCLUSION

In this paper, we have proposed a context-based adap-

tive hard thresholding to overcome the shortcoming of using fixed hard thresholding in BM3D. Experimental result shows that we have achieved significant improvement over the original algorithm. However our algorithm requires training classifiers, hence the time complexity is higher than the original BM3D. Once the machines are trained, it requires little amount of time to predict the label of each image block and hence the time complexity is similar to BM3D. In future, we will continue our work to adaptively adjust other fixed parameters used in BM3D. Also, we will extend our idea to denoise color image and video sequences also.

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