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Multiclass Noisy Image Classification Based on Optimal Threshold and Neighboring Window Denoising

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Abstract

Classification of multi class images is very enviable for different recognition. This is affected by many factors such as noise, blur, low illumination, complex background, occlusion etc. Noise is one of the major factors causing degradation of the classification performance. This paper proposes an efficient method for classification of multi class object images which are corrupted by Gaussian noise. A wavelet transform based denoising scheme by thresholding the wavelet coefficients namely *NeighShrink* has been utilized to eliminate too many wavelet coefficients that might contain noise information and selecting useful coefficients. This work shows robustness of proposed method of multiclass object classification over the spatial domain denoising and feature extraction method for classification.

Keywords
Wavelet, Neighborhood window, Hard and soft thresholding, multi class, neural network.

1. Introduction

Image Classification, event detection and video summarization are the main problems of interest in building of next generation multimedia system for content based image retrieval system. Multi class image classification is very important work in analysis of images. This plays a significant role in several computer vision applications such as content based image retrieval, automated visual inspection, biomedical image processing and remote sensing applications. Although so many researchers have worked in semantic classification of visual information but hardly anyone had considered classification of noisy images. Since noise affects the performance of the classification, so method of features selection would be an important step.

Image classification algorithms can be designed by finding essential features which have strong discriminating power, and training the classifier to classify the image. Researchers have done enormous effort in progress of advanced classification approaches and methods for enhancing classification performance ([1-6]).A patch-based sparse texton learning method of texture classification is presented in [7]. The classification of texture images [8] is performed using dominant neighborhood structure, where global features of the image are extracted. Local binary patterns (LBPs) are extracted next in order to provide supplementary local texture features to the generated features from the principal neighbourhood structure. Gray Level Co-occurrence Matrix (GLCM) based Texture classification system is presented in [9]. Gray Level Co occurrence matrix is calculated from the original texture image and the differences calculated along the first non singleton dimension of the input texture image. Different texture images are classified based on wavelet texture feature and neural network in [10].

The learning process is achieved through the modification of the connection weights between units. The work [11] presents multi spectral classification of land-satellite images by means of neural networks. The classification of war scene by means of a back propagation neural network is presented in the work [6]. A comparison to conventional supervised classification by using minimal training set in Artificial Neural Network is given in [12]. Performance of the classification tool is analyzed in defect identification in plywood with traditional minimum distance classifier and artificial Neural Network [13]. Choosing the threshold value is a very important in these methods. Currently a large amount of research is being performed on selection of threshold value for denoising [16-17].

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Mostly images are corrupted by Gaussian noise during the acquisition of the image in camera. One of the most powerful methods for denoising the 2D images is demonstrated through wavelet analysis [14]. The denoising method is applied on wavelet coefficients obtained through performing discrete wavelet transform of noisy image at different scale. Wavelet transform of noisy images show that the small coefficients are due to noise and large coefficients are more likely due to important image features [14, 15]. A number of thresholding based denoising methods have been presented by different researchers.
This paper deals with the classification of noisy images of multiclass. Here a thresholding based noise reduction method is used for robust feature extraction. This work is mainly divided into two experiments, object classification of noisy images and object classification of images without noise. This paper is mainly constitutes four sections. Section 2 presents a noise reduction method using wavelet thresholding. Section 3 describes the GLCM features representation of subband images produced after noise removal. Section 3 and 4 demonstrate the proposed method and simulation result.

2. Thresholding Based Noise Reduction

Suppose $f(x,y)$ is a original image and $g(x,y)$ be corrupted by Gaussian white noise $n(x,y)$ with zero mean. Then the degradation process of an image can be modeled by the following eq 1 as described in [18, 19].

$$g(x,y) = f(x,y) + \sigma\, \mathrm{n}(x,y) \tag{1}$$

where σ is point spread function.
Wavelets are mathematical functions which assist in relating the image into frequency domain, which can further be divided into subband images of different frequency components as presented in fig 1. Wavelet denoising schemes are implemented using soft thresholding and hard thresholding. This procedure of denoising works well in different applications because wavelet transform has the compaction property i.e. it has large coefficients in small number. Thresholding is a non-linear operation applied to each wavelet coefficients. Due to the linearity of the wavelet transform the additive noise model in the image domain remains additive in the transform domain as well

$$NO_{k,d}(x,y) = NF_{k,d}(x,y) + NC_{k,d}(x,y) \tag{2}$$

where $NO_{k,d}(x,y)$, $NF_{k,d}(x,y)$, $NC_{k,d}(x,y)$ are noisy, noise free wavelet coefficient and noise components [26], [27] [32]. Scale and orientation of wavelet coefficients are denoted by k and d. If summation of squared coefficients of the local window is less than or equal to γ^2 then the wavelet coefficient $NO_{k,d}(x,y)$ are set to zero otherwise we shrink it according to

$$NO_{k,d}(x,y) = NO_{k,d}(x,y) \times \langle 1 - \frac{\gamma^2}{S^2(x,y)} \rangle \tag{3}$$

$$\gamma^2 = 2\sigma^2 \log n^2 \tag{4}$$

where $S^2(x,y)$ is summation of squared coefficients of the local window as shown in the Fig 2, σ^2 standard deviation of the coefficients and n is size of the local window.

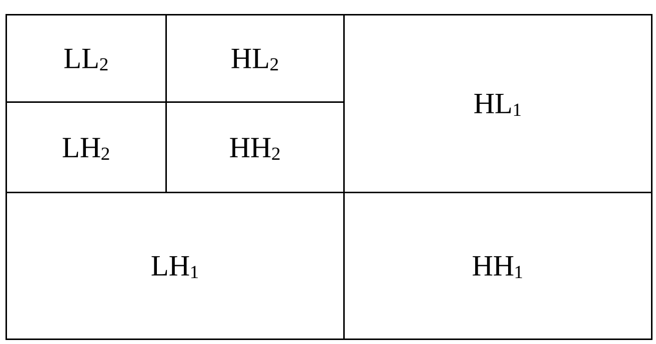


Fig 1: 2 Level Discrete Wavelet Transform

3. GLCM Textural features

A new texture based segmentation algorithm which uses a set of features extracted from Grey-Level Co-occurrence Matrices [34]. Gray level co occurrence matrix (GLCM) based texture features are computed using FPGA hardware level [24].This work basically enhanced the computational speed and produced better results of pattern recognition. This hardware architecture of FPGA was improved in the work [25] for more efficient computation. Researchers have improved the efficiency of fingerprint matching by combining GLCM based feature extraction with Euclidean based matching [35].

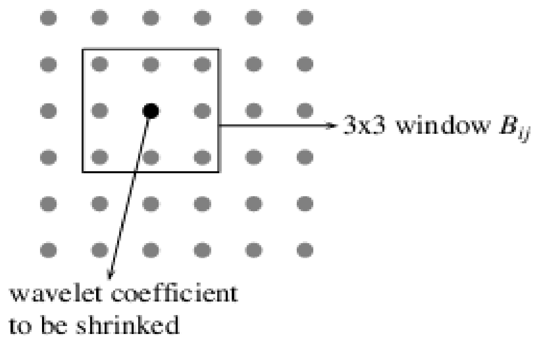


Fig 2: An example of neighboring window centered at the wavelet coefficient [26]

Gray Level Co occurrence Matrix defines the spatial relationship of one gray level with another gray level in a specified area [25]. Here the GLCM is calculated using two parameters i.e. relative distance between two pixels d in terms of pixel number and their relative orientation φ [25].Normally the orientation angles φ are considered in four directions 0^0, 45^0, 90^0, 135^0. GLCM $C_{m,n}$ for distance d and direction φ is given [25] as

$$C_{m,n} = \sum_x \sum_y P\{I(x,y) = m \ \& I(x \pm d\varphi_0, y \mp d\varphi_1 = n\} \tag{5}$$

Where P{.}=1 if the argument is true otherwise it is 0. For the value of φ as 0, φ_0 and φ1 are referred as 0 and 1 respectively, for φ as 45, φ_0 and φ1 are referred as -1, -1, for φ as 90, φ_0 and φ1 are referred as 1, 0, and for φ as 135, φ_0 and φ1 are referred as 1, -1. In the paper [25], Haralick et al. presented 14 texture features from GLCM and considered six as most significant. These are as energy, entropy, contrast, variance, correlation and inverse difference moment.

Suppose $P(i,j,d,\varphi)$ is frequency of occurrence of gray level pair (i,j) at distance d and angle φ and η_g be the no of gray levels

$$Contrast = \sum_{i=1}^{\eta_g} \sum_{j=1}^{\eta_g} (i-j)^2 P(i,j) \tag{6}$$

$$Correlation = \sum_{i=1}^{\eta_g} \sum_{j=1}^{\eta_g} \frac{(i-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x \sigma_y} \tag{7}$$

$$Entropy = -\sum_{i=1}^{\eta_g} \sum_{j=1}^{\eta_g} P(i,j) \log P(i,j) \tag{8}$$

$$Energy = \sum_{i=1}^{\eta_g} \sum_{j=1}^{\eta_g} P(i,j)^2 \tag{9}$$

Where μ_x , μ_y , σ_x , σ_y the means and variances of the rows and column sums respectively are defined as follows

$$\mu_x = \sum_{i=1}^{\eta_g} \sum_{j=1}^{\eta_g} i \, P(i,j) \tag{10}$$

$$\mu_y = \sum_{i=1}^{\eta_g}\sum_{j=1}^{\eta_g} j\, P(i,j) \tag{11}$$

$$\sigma_x = \sqrt{\sum_{i=1}^{\eta_g}\sum_{j=1}^{\eta_g}(i-\mu_x)^2 P(i,j)} \tag{12}$$

$$\sigma_y = \sqrt{\sum_{i=1}^{\eta_g}\sum_{j=1}^{\eta_g}\left(i-\mu_y\right)^2 P(i,j)} \tag{13}$$

4. Proposed Work

The key points employed in proposed system, are discussed in preceding sections. This section discusses how the above concepts are implemented. Generally any classification system consists of preprocessing, feature extraction, training and testing phases. Since the presence of Gaussian noise corrupt the important features of the object image, the effect of noise is to be minimized. This process is carried out by thresholding the various wavelet coefficients of image using optimal thresholding algorithm [27], which is followed by feature extraction and supervised learning using Back Propagation Neural Network (BPNN) to predict the class of test image. Fig 3 describes the major steps involved in this classification system. Feed forward neural network takes input as feature vector to produce the class of the input image. The performance of the system is evaluated by conducting two experiments. In the first experiment multiclass object classification without presence of noise is carried out and second experiment classifies noisy images.

4.1 Data Set

The performance of the proposed model is evaluated with the database taken from Columbia Object Image Library (COIL-100) [29]. COIL-100 is database containing colored images of hundred classes. Sample images of the sixteen classes utilized in this work from COIL-100 library are shown in the fig 4. These color images are converted into grayscale image in the beginning. The first experiment is carried out on data set containing 3200 images without noise, where each object class contains 200 images. Out of these 3200 images 50 of each class are used for training and 150 images of each class for testing the performance of the classification model. Then a noisy image database is prepared by introducing Gaussian noise for the different value of variance in the range of 0.0 to 0.8 and zero mean This way a database of 2400 synthetic images i.e. 150 images of each category is developed for the second experiment. Sample noisy images with different values of variance are shown in the fig 5.

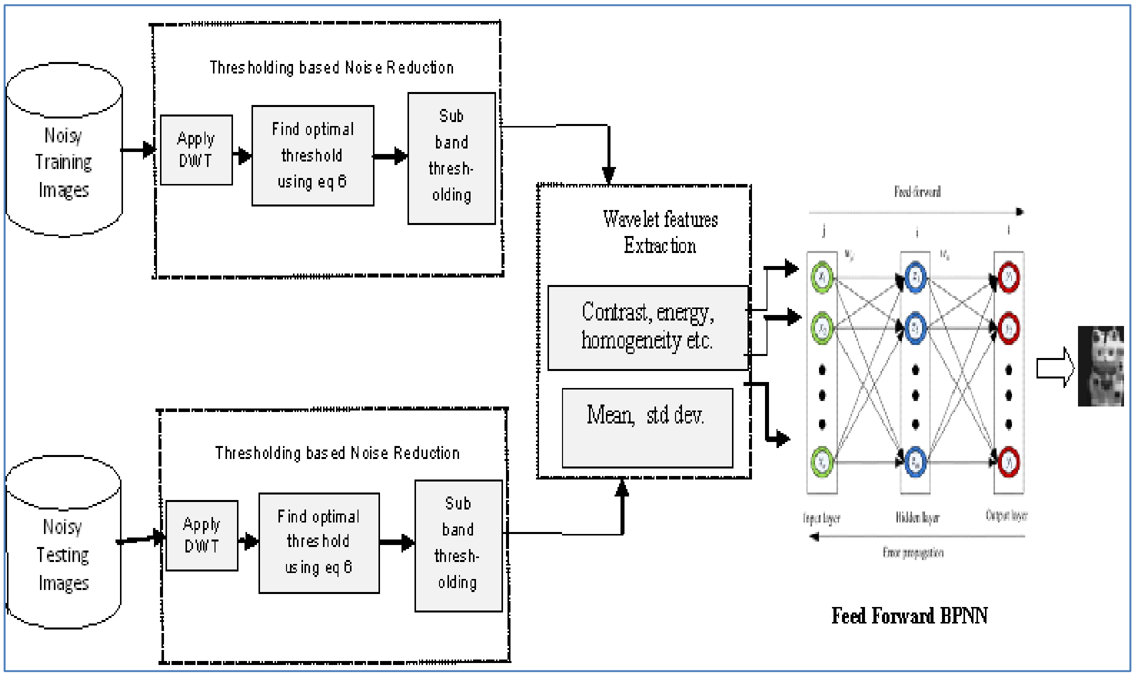


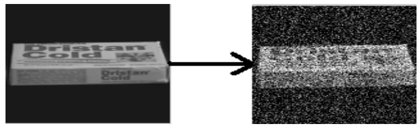
Fig 3:System Model for noisy image classification

4.2 Wavelet Based Noise Reduction

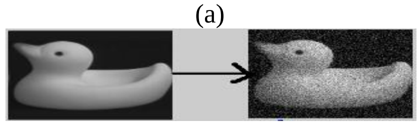
Chen et al. [26] applied Neighbor Coefficients to image denoising and their method is called as NeighShrink. In this algorithm of denoising noisy wavelet coefficients are shrinked, where a square neighboring window B is centered at it. Neighboring window size $n \times n$ is considered where n non negative odd integer. This method of noise reduction starts with 2D wavelet transform of noisy object image. Wavelet transform decompose a 2D image into four frequency subbands, namely, LL, LH, HL, and HH at every level. In next level, wavelet transformation is applied to the low frequency subband LL only.

Fig 4: Sample Images of 16 categories form COIL-100 database

In this work, wavelet decomposition has been applied upto two levels only. Since the low frequency wavelet coefficients would be retaining the average Gaussian noise components, so wavelet coefficients of the high frequency sub bands are required to be thresholded [32]. So we need to threshold all LH, HL, and HH within these high frequency subbands.



(a)



(b)

Fig 5: Gaussian noise corrupted original image with different variance and zero mean (a) var= 0.09 (b) var=0.02

We need to consider a neighbourhood window B around for every wavelet coefficient of high frequency subbands. The window is chosen by including the same number of pixels above, below, and on the left or right of the pixel to be thresholded. Which means the neighbourhood window size should be 3 × 3, 5 × 5, 7 × 7, etc. Fig 2 illustrates a 3 × 3 neighbourhood window centered at the wavelet coefficient to be thresholded. Different wavelet coefficient subbands have been thresholded independently.

$$S^2(x,y) = \sum_{x,y\in B} NO^2(x,y) \tag{14}$$

When the above summation has pixel indices beyond the coefficient matrix, the corresponding terms in the summation are not considered. For the wavelet coefficient to be thresholded, the shrinkage is performed according to the following:

$$NO_{k,d}(x,y) = NO_{k,d}(x,y) \times \alpha(x,y) \tag{15}$$

where shrinkage factor can be described by

$$\alpha(x,y) = 1 - \frac{\gamma^2}{S^2(x,y)} \tag{16}$$

$$\alpha(x,y) = \alpha(x,y) \quad if\ \alpha(x,y) > 0 \tag{17}$$

$$\alpha(x,y) = 0 \quad if\ \alpha(x,y) < 0 \tag{18}$$

The above process produces the detailed coefficients with reduced noise components. Which can be further used to produce feature space in the next phase of the classification system. In this experiment noisy images of size 128×128 are decomposed upto two levels using discrete wavelet transform function. This produces horizontal, vertical and diagonal coefficients matrix of size 64×64 and 32×32 in scale 1 and scale 2 respectively.

4.3 Feature Extraction

The procedure discussed in the above section produce the various coefficient matrixes containing the edge information of the image. These coefficient matrixes can be used to extract important features of the object image. GLCM based descriptors are used to represent the object information. Texture information such as Contrast, Correlation, Entropy and Energy are calculated from the subband images produced by level 1 and level 2 of wavelet decomposition using equations 10,11,12 and 13 respectively. The steps in feature extraction process are repeated for the Horizontal, Vertical and Diagonal coefficients matrixes as follows

Step 1. Compute four Gray Level Concurrence Matrix for the angles $\varphi=0^0$, 45^0, 90^0 and 135^0.
Step 2. For every GLCM matrix produced in step 1 calculate the value of Contrast, Correlation, Entropy and Energy [25].
Step 3. Calculate the mean of the Coefficient matrix
Step 4. Compute the standard deviation.

This process generates a feature vector containing 108 descriptor [4 GLCM matrix **X** 4 values for each GLCM matrix **X** 6 Coefficient matrixes for scale 1 and scale 2 + 12 (mean and std deviation for 6 coefficient matrix)]. Then feature vectors of each of the image are arranged into matrix, called as feature matrix. Feature matrixes are used for training and testing of the neural classifier.

4.4 Classification using Neural Network

The performance of any classification system significantly depends on the choice of the particular classifier. Artificial Neural Network architectures are increasingly employed in successful image classification schemes as presented in the works ([10],[30],[31],[32],[33]) using Back Propagation Neural Network (BPNN). ANNs are formulated of neurons that work as collective unit which are basically interconnected processing units. This establishes a relationship between inputs and outputs by identifying patterns. While training of the neural network a pair of pattern (I_k, T_k), where I_k and T_k are the input and target pattern. The I_k pattern produces a output responses to each neurons in each layer and an output OP_k at output layer. The difference between actual and desired output produce an error signal. This error significantly depends on the values of the neurons. Any BPNN learning algorithm will required the following at the beginning

- Training patterns, Input pattern and desired output pattern
- Learning rate
- Some criteria for termination of the algorithm
- A method for weight modifications
- Sigmoid function
- Initial Weight values

The goal of the BPNN algorithm is to minimize this error, until the neural network learns the training data. This can be implemented by:

$$\Delta w_{ji}(n+1) = \rho\left(\gamma_{kj}\emptyset_{pj}\right) + \delta\Delta w_{ji}(n) \qquad (19)$$

Where ρ is the learning rate, δ is momentum, γ_{kj} is the error and n is the number of iteration.

5. Simulation and Results

The performance of this method of feature extraction is evaluated on two ways i.e. in noiseless images and with noise. The feature extraction method is simulated in two experiments as

5.1 Experiment 1: Object Classification in Noiseless Images

This experiment starts with conversion from RGB to gray scale and resizing of original images to 128X128 pixels, which is followed by features extraction by the method described in section 4.3. It produces a feature matrix of size 108X800 for training. Similarly a feature matrix of size 108X2400 is produced from test images. Then a neural classifier is designed with ten hidden layers and 16 output layers as shown in fig 6.

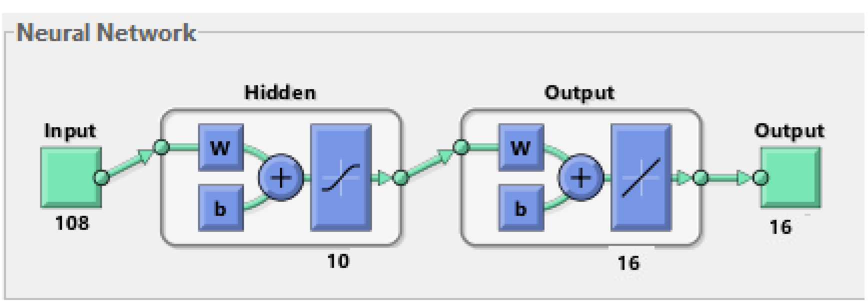


Fig 6: Architecture of Neural Classifier for the proposed method

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The training process is continued till the best validation performance achieved. The training stopped when the validation error increased for 6 iterations as shown in the performance graph fig 6. The best validation performance is achieved at 17^{th} epoch.

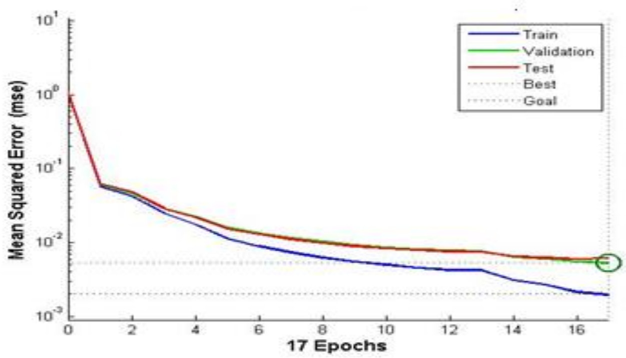

Fig 7: Performance of Neural Classifier for Experiment 1

The feature matrix of test images are applied to trained neural network for classification. The results produced by the classifier are as confusion matrix. These values of confusion matrix are used to calculate statistical metrics as Precision, Recall and Specificity and recorded in table 1.

5.2 Experiment 2: Object Classification in Noisy Images

Another experiment is carried out to analyse the performance of the object classification system in noisy images. Images are decomposed using wavelet transform for reduction of noise using the method described in section 4.2, which is followed by feature extraction presented in section 4.2 and 4.3. It produces a feature matrix of size 108×2400 from test images. Then a neural classifier created and trained in experiment 1 is utilized for classification of this set of noisy images.

Table 1: Classification Results

Classification Result for Experiment 1				Classification Result for Experiment 2		
Object Class	**Precision**	**Recall**	**Specificity**	**Precision**	**Recall**	**Specificity**
C1	92.8	94.6	99.5	94.6	93.3	99.6
C2	95.4	98	99.7	96	96.0	99.7
C3	97.4	100	99.8	96.1	99.3	99.7
C4	99.3	95.3	99.9	99.3	95.3	99.9
C5	97.2	94.7	99.9	97.2	93.3	99.8
C6	95.4	96.7	99.7	94.6	93.3	99.6
C7	96.7	97.3	99.8	98	97.3	99.8
C8	96.6	94	99.8	96.5	94.0	99.8
C9	94.2	97.3	99.6	93.4	94.6	99.5
C10	97.3	95.3	99.8	97.2	95.3	99.8
C11	93.5	96	99.5	91	94.0	99.4
C12	96.1	98.7	99.7	95.5	98.7	99.5
C13	97.3	96.7	99.8	94.7	94.7	99.6
C14	94.2	98	99.6	92.3	96.7	99.5
C15	98.6	95.3	99.9	95.3	95.3	99.7
C16	95.3	96	99.7	94.6	94.0	99.6
Classification Accuracy			**96.5**	**Classification Accuracy**		**95.3**

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The feature matrix of test images are applied to trained neural network for classification. The result produced by the classifier is confusion matrix. These values of confusion matrix are used to calculate statistical metrics Precision, Recall and Specificity and recorded in table 1.

5.3 Result Discussion

The noisy image database and the number of images for training and testing have been discussed in preceding sections. Optimal structure validation is performed by conducting several experiments with different parameters of the neural classifier system. The structure of neural network given in the figure 6 performs well and leads to better results. The various parameters for the neural classifier training using statistical features for noisy images are given in table 2.

Table 2: Neural Network parameters for training

Parameters	**Experiment 1**	**Experiment 2**
Neural Network Structure	108-10-16	108-10-16
Learning Rate	0.05	0.05
Performance Goal	0.02	0.02
Classification Accuracy	**96.5**	**95.3**

The performance of the system proposed in this work is compared with the work discussed in [23], where the effect of noise in classification of COIL-100 object images is investigated. This paper [23] presents the classification rate in three different experiments, classification of sixteen categories images without noise, in presence of Gaussian noise and after spatial filtering by Wiener filter. Table 3 present a comparison of the current system with classification accuracy of the original images and the effect of spatial domain filtering before feature extraction in the work [23].

6. Conclusion

In this paper an effort has been made to classify large number of object categories in presence of noise. A wavelet based method of feature extraction of noisy images is presented. The performance of the approach is examined under two different constraints, in presence of noise and without noise. The bar chart shown in fig 8, reveals that wavelet based approach is able to reduce the effect of noise in object classification by achieving 95.3 percent of accuracy while in the case of without noise as 96.5 percent.

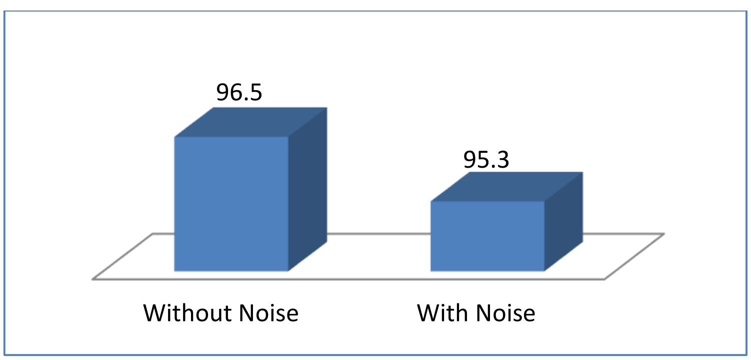

Fig 9:Performance Comparison

The classification accuracy obtained in the current work is compared with previous work[23]. This research work classifies large number of object classes in presence of Gaussian noise and after noise removal in spatial domain. The current method of classification of the noisy images presents robustness over this method. It is clear from the results shown in the table 3 that wavelet based method of noise removal and feature extraction gives a robust performance.

Table 3: Comparison of Proposed system with [23]

Image Class	**Classif Accur. (without noise) [23]**	**Classif Accur. (Noisy Images) [23]**	**Classif Accur. of Current Method (Noisy Images)**
1	86.8	59.9	**93.95**
2	90	66.5	**96**
3	90	62.3	**97.7**
4	77.2	61.9	**97.3**
5	78.2	70.5	**95.25**
6	76.8	69.6	**93.95**
7	83.2	63.2	**97.65**
8	78.65	66.4	**95.25**
9	86.4	38.6	**94**
10	86.9	56.4	**96.25**
11	88.1	52.9	**92.5**
12	82.6	37.5	**97.1**
13	84.8	68.5	**94.7**
14	88.3	76.5	**94.5**
15	86.4	69.8	**95.3**
16	82.1	81.5	**94.3**

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